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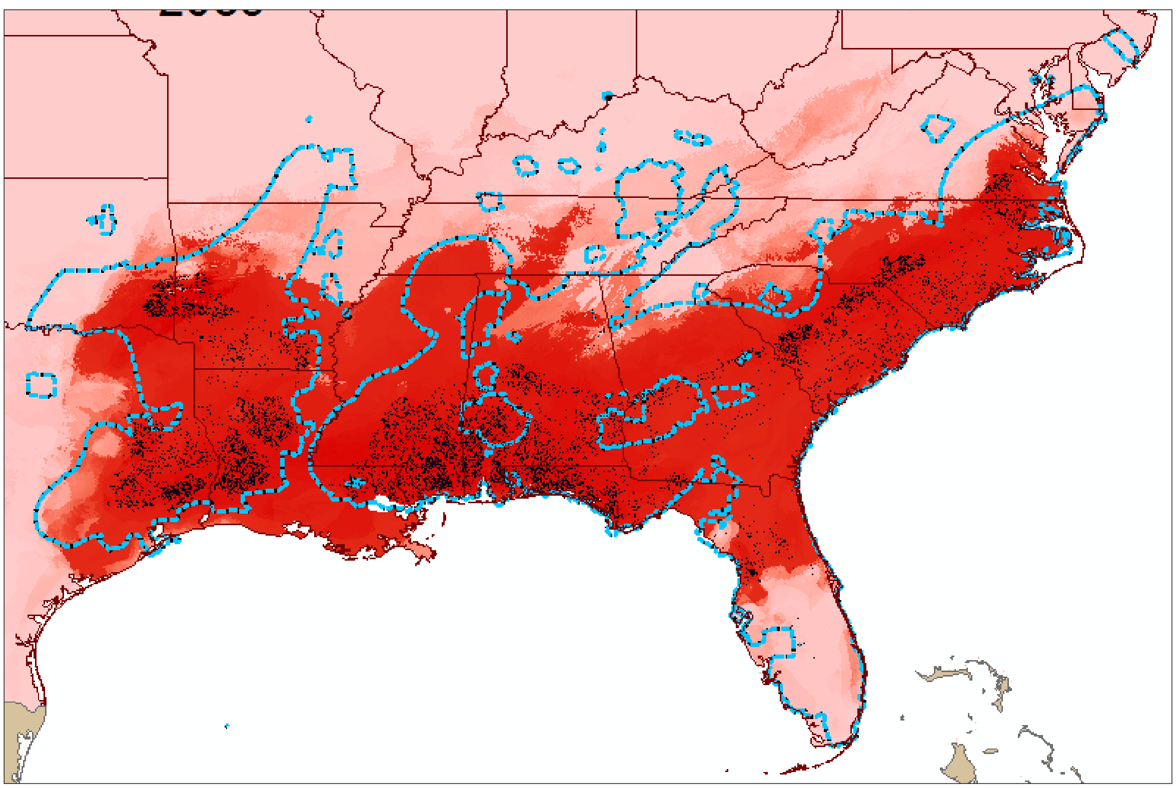
Application of Maxent Multivariate Analysis to Define Climate-Change Effects on Species Distributions and Changes

Robert C. Lozar and James D. Westervelt

September 2014



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Robert C. Lozar and James D. Westervelt

Construction Engineering Research Laboratory
US Army Engineer Research and Development Center
2902 Newmark Drive
Champaign, IL 61822

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Abstract

Army installation managers and planners have limited sources of scientifically reliable information that can be used to examine potential climate impacts on local flora and fauna. The present work evaluated the viability and versatility of applying statistical multivariate analysis to define the current and projected future range probability for species of interest to Army land managers. A software program called Maxent was used to perform range-extent analyses for two animal species of interest to Army land managers: the Red-Cockaded Woodpecker (RCW) and the common musk turtle. The technology was used to determine how climate change might affect species thresholds of survival at Army installations. The software data input requirements and output capabilities are described. The analytical methodology applied to the study of both species is discussed in detail, and validation of results is addressed.

The authors conclude that Maxent analyses can provide impartial, data-based results that reflect scientific consensus on related climate-change issues while avoiding emphasis on the extremes of scientifically collected data. Analysis results indicate that climate change will alter RCW habitat threshold values on some installations beyond the point where Army-managed mitigation is possible. In contrast, musk turtle habitat will increase at least until 2025.

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Preface

This study was conducted for the Office of the Assistant Secretary of the Army for Acquisition, Logistics, and Technology (ASA(ALT)) under Research, Development, Test, and Evaluation Program Element 896, "Base Facilities Environmental Quality; Project 335114, "Climate-Change Effects on Natural Resources." The technical monitor was Dr. Alan B. Anderson, Technical Director, CEERD-CV-T.

The work was performed by the Ecological Processes Branch (CN-N) of the Installations Division (CF), US Army Engineer Research and Development Center, Construction Engineering Research Laboratory (ERDC-CERL). This project was managed as part of the "Prediction and Adaptation of Military Natural Infrastructure in Response to Climate Change" work package under the direction of Dr. Timothy Hayden. At the time of publication, William D. Meyer was Chief, CEERD-CN-N; Michelle J. Hanson was Chief, CEERD-CN; and Dr. Alan B. Anderson was the Technical Director for Military Ranges and Lands. The Deputy Director of ERDC-CERL was Dr. Kirankumar Topudurti and the Director was Dr. Ilker Adiguzel.

COL Jeffrey R. Eckstein was the Commander of ERDC, and Dr. Jeffery P. Holland was the Director.

1 Introduction

1.1 Background

Climate model projections summarized in the 2007 Intergovernmental Panel on Climate Change report (IPCC 2007a) indicate that global surface temperature is likely to rise between 1.1 and 6.4 °C during the 21st century. In February 2010, in response to climate-change forecasts, the President's Council on Environmental Quality (CEQ) issued draft guidance to all Federal agencies concerning the manner in which climate change should be included in the evaluation of environmental effects under the National Environmental Policy Act (CEQ 2010).

> Agencies should consider the specific effects of the proposed action (including the proposed action's effect on the vulnerability of affected ecosystems) . . . .

The Quadrennial Defense Review (QDR) was the first Department of Defense (DoD) publication (QDR 2010) to address the issue of the growing need to consider risks and response strategies for climate change. In the QDR, the DoD explicitly acknowledged that climate change will likely affect the nature and scope of future missions, as well as training and testing assets of military installations.

Climate change issues are being addressed in the Army's Integrated Natural Resources Management Plan (Legacy 2009). The purpose of the management plan at an installation is to enable planners to implement landscape- or ecosystem-level management and to coordinate with other stakeholders in the region, over time periods reflecting that natural communities require multiple decades to mature and evolve. The goal the integrated and local plans is to ensure good resource stewardship that is compatible with no net loss of land necessary to support the military mission.

Army installation managers and planners have limited sources of scientifically reliable information that can be used to examine potential climate impacts on local flora and fauna. Most literature examining climate-change effects on military installations to date has dealt with impacts of rising sea levels on coastal areas, a concern more important to Navy and

Marine Corps operations than Army installations. However, the authors have performed a series of previous studies examining climate-related impacts on the ecosystems of various installations (Lozar 2011 2012a, 2012b, 2013, Westervelt 2011).

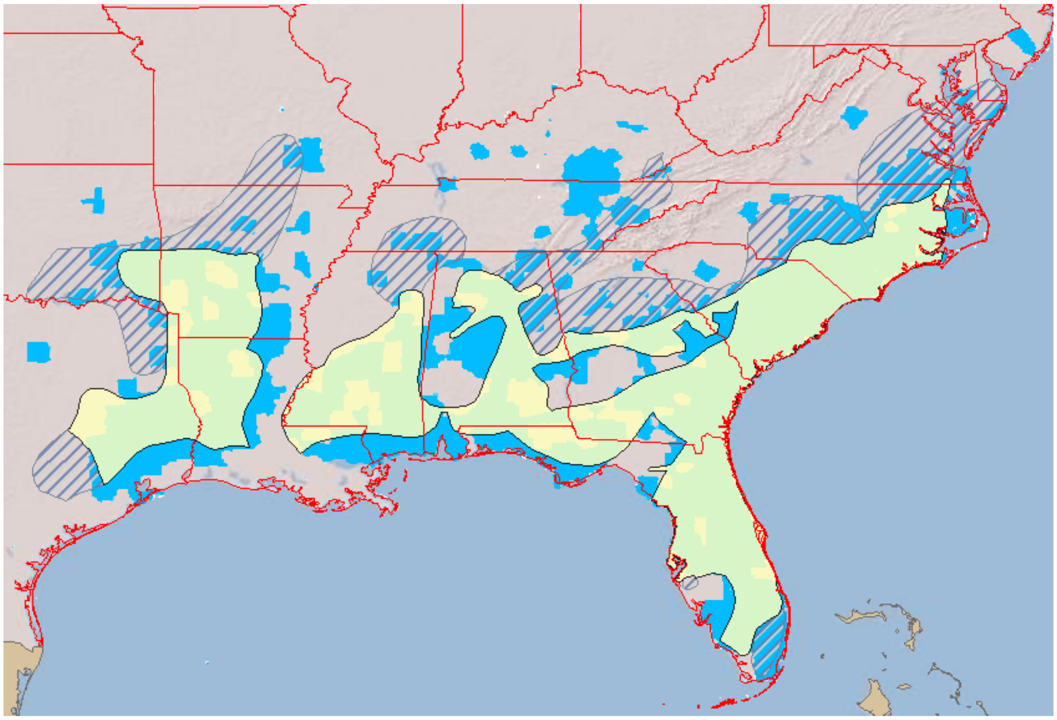
The present study was funded under Research, Development, Test, and Evaluation Program Element A896, "Base Facilities Environmental Quality," as part of a work package entitled "Prediction and Adaptation of Military Natural Infrastructure in Response to Climate Change." The overall purpose of the work in part is to

> analyze the influence of climate change on environmental impacts of interest to military planners and decision-makers. The analytical framework integrates rigorous, large-scale models of the global climate system with analytically tractable model linkages to regional assessments of climate change, weather, ecological stressors, watershed processes, and landscape evolution.

The most basic question to be answered is, "What climatic factors current and future determine the probability range of species of interest to the Army at a given installation?" The present work evaluated the viability and versatility of applying statistical multivariate analysis to answer this question.

An initial assumption in research design was to begin with established knowledge of species extent as a geographical basis for predicting impacts driven by a set of temporally changing bioclimatic characteristics. Starting with one species of high interest, the red-cockaded woodpecker (RCW), several different documented "standard" ranges were found in the literature. Figure 1 shows two "standard" RCW ranges that differ significantly. Study could arguably begin with the potential range, or the current plus previous range, or even locations where the species has been sighted. Predictably, preliminary modeling incorporating this kind of conflicting range information produced incoherent results. Problems that soon became obvious resulted from issues such as multiple conflicting definitions of single-species range, sightings that did not result from systematic professional surveys, absence data that might reflect absence of observations rather than absence of species, misidentified species sightings, and sightings from various different time periods.

Figure 1. Plots of contradictory RCW range data.



Notes: Yellow areas show current RCW range and hatched areas represent previous range (NatureServe 2013). Blue areas indicate county locations of RCW habitat determined by Jackson (1971) and Hooper et al. (1980).

Existing sources of information on species extent are not uniformly accurate because distributions have been modified by agriculture and urbanization. Historical data are spotty and inconsistent, and historic sightings by county are not the results of a professional systematic survey. The multiple sources examined for RCW distributions present several questions:

- Does land-use change make a difference to the potential range of the RCW?
- Is population in some areas overweighed because of data redundancy?
- Is the presence of outlier counties real, or is the species misidentified in those locations?
- Are holes in the coverage real, or just due to lack of observation?
- Are the denser clusters of sightings due to greater species density or due to a clustering of observers?

Such problems pertain not only to RCW data, but potentially to any species of interest. These observations and questions make it obvious that an alternative methodology is needed to provide objectivity and consistency in the definition of species range before climate-change impacts can be effectively studied.

Most basic data about a species occurrence takes the form of individual sightings, but rarely is a lack of sighting equivalent to the absence of a species. Therefore, the work focused on ways to define distribution based on presence-only techniques, of which several are established. BIOCLIM, the online climate database accessible at http://worldclim.org/bioclim, predicts suitable conditions in a "bioclimatic envelope" of observed presence values in each environmental dimension (Busby 1986, Nix 1986). DOMAIN, a modeling procedure for mapping potential distributions of plants and animals, uses a "similarity metric" that produces a predicted suitability index by computing the minimum distance in environmental space to any presence record (Carpenter et al. 1993). GARP, a genetic algorithm approach for creating ecological niche models for species, has been applied to several presence-only studies (Anderson 2003, Joseph and Stockwell 2002, Peterson and Kluza 2003, Peterson and Robins 2003, Peterson and Shaw 2003).

Multivariate analysis is the basis of modeling software package called Maxent (Phillips 2006), which applies a multivariate technique called *maximum entropy analysis*. In this context, "entropy" is a measure of image information content. Maxent is designed to determine the maximum information content expressed by the data that is input using a technique deriving from the Second Law of Thermodynamics. This multivariate approach can be applied to define species range of extent. The program develops an unbiased probability distribution on the basis of partial knowledge. In addition, it offers a suite of statistical analysis tools that are highly useful in evaluating the quality of the resulting range map and ancillary outputs.

1.2 Objective

The objective of this study was to test and evaluate the capability of multivariate analysis using Maxent software to determine how climate change might affect species thresholds of survival at Army installations.

1.3 Approach

The bioclimatic data used to do the analysis are described in some detail, both in terms of their validity and suitability for application in the analysis. Also, the salient features of Maxent analysis are explained.

After each analysis was run, the outputs were evaluated in terms of their statistical viability, and various sensitivity tests were applied. The particular focus was on how the major analyses would affect two species of interest on Army lands: the Red-Cockaded Woodpecker (*Picoides borealis*) and the common musk turtle (*Sternotherus odoratus*). The Red Cockaded Woodpecker is a threatened/endangered species (TES) that nests in pine trees of the United States southeastern region. Its presence on military installations requires that federal land managers set aside tracts of land for the species preservation and augmentation. The issue that results from their presence is that these lands may also be desirable for the purposes of military training and testing; conflicts may arise. In the face of climate change, installation planners need to know what might happen to the species and how that may affect the planner's need to manage training lands with the appropriate financial resources. The common musk turtle is a familiar amphibian species that ranges throughout the Eastern United States. Its preservation is less problematic for the Army, so it provides a good complement to the TES species analysis.

1.4 Scope

The primary thrust of this work was to examine the affects of climate change on species of importance to Army land managers. To accomplish this it was necessary to generate species distributions and comparable changes in those distributions over time. Those distributions were generated using a rigorous statistical approach. However, the primary goal did not include the submission of a new standard distribution map for each species studied; the distribution maps were a means to achieve the end of defining effects of climate change.

This investigation inspects currently available data and analysis techniques. The authors did not attempt to generate new climatic predictions or to program new software. Also, this report deals with scientifically validated climate-change data, not data on weather or weather extremes. Furthermore, it is assumed that military missions at installations will remain the same as they are today.

1.5 Mode of technology transfer

With the demonstrated utility of the maximum entropy approach for spatially identifying areas that are suitable for a given purpose, based on known suitable areas, this approach is now being applied in other studies.

We are currently using the methodology to study the current and forecast habitat extents for a variety of reptiles (three turtle and four snake species) that live in the southeastern United States. Controlled laboratory studies are being performed to validate the identification of climate thresholds for several of these species. The method is also being applied to the study of climate-change-induced modifications to ecosystems around military installations, with the goal of illuminating the potential for ecosystem shifts in response to climate change. The method also will be applied to understand and forecast urban security issues associated with megacities in developing countries.

2 Data and Analytical Tools

2.1 Selection of climate change data

Research scientists are particularly sensitive to the issue of choosing data biased toward a particular predisposition. Although military groups do have preferred data sets for climate change research, the authors were very careful to follow guidelines in the choice of data that would assure the greatest viability and overall acceptance. These guidelines included using data:

- generated by others with more expertise than the authors
- from independent sources
- generated in a well documented, industry-accepted manner
- that are freely available to all so that this research can be easily and accurately replicated.

The most widely accepted global climatic models (GCMs) all generate predictions based on a set of conventions disseminated through the IPCC. Such standardization is meant to facilitate comparison between models. The IPCC reports (IPCC 2007b) are intended to reflect the scientific consensus among the experts in the field. All data used in this research follow the IPCC standards.

The IPCC has established a series of standard future scenarios to assist with coordination and comparison between modeling efforts. This international standard set of scenario types is named after the Special Report on Emissions Scenarios (SRES). The SRES was prepared by the IPCC for the Third Assessment Report (TAR) in 2001 on future emission scenarios to be used for driving GCMs to develop climate change scenarios. The SRES were also used for the Fourth Assessment Report (AR4) in 2007. For this study, the following SRES were used:

- A1(B): globally homogenous rapid economic growth (with B variation = a balanced usage of both fossil and non-fossil fuel energy sources.
- A2: locally heterogeneous, regionally oriented economic growth
- B1: globally homogenous sustainable economic growth.

Twenty-one major GCMs were prepared while participating in AR4. For this research, those models having the greatest number of validation studies and those with the longest-period of development (10–20 years) were used. They are:

1. GFDL Model - NOAA Princeton (gfdl_cm2_1)
2. NASA GISS (giss_model_er)
3. United Kingdom Hadley Model (ukmo_hadcm3)
4. Canadian (CCCma) Model (cccma_cgcm3_1_t47)
5. NCAR Boulder (ncar_ccsm3_0)
6. Australian Model (csiro_mk3_5).

The most recent model results (the AR4) were used in this study.[1]

2.1.1 Climate data characteristics

The GCM data used here has been downscaled or refined from their initial resolution by integrating into it more local concerns such as topography, surface winds, evaporation, and local precipitation[2]. Downscaling using statistical approaches produces bits of information down to 30 arc-seconds (~0.8 km) on an edge. It is this scale data used here.

The data used have been averaged over a 30 year period. In this report, for purposes of brevity, we refer to an entire period using its midpoint date. For example the period of 2010–2039 is referred to as "2025".

To represent "current" conditions, we used the WorldClim, dataset which represents downscaled data from weather stations averaged over a period of 1950–2000 (available directly from the WorldClim site at http://www.worldclim.org/current). In this report, whenever the term "current" is used, it will refer to these WorldClim data as the 1990 data set.

The International Centre for Tropical Agriculture (CIAT) has downscaled predictive climate projections from the IPCC. At 30 arc-seconds resolution, its degree of detail is comparable to the resolution of the current WorldClim data.

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1 AR5, the Fifth Assessment Report is in progress at the time of this writing. While the data is just becoming available, the types available are not nearly as mature as those based on the AR4 work. http://www.ipcc-wg2.gov/AR5/ar5.html.

2 Basic information from http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/dcpInterface.html.

For each of the time intervals, the 18 layers (from the 6 GCMs and three scenarios) that represent the time interval were averaged together. By this action, the data used in this research represent the scientific consensus of the best models available. This selection also should avoid the controversy that seems to emerge when extreme values from one model are unfavorably compared with those of another model. Finally, it simplifies and clarifies the task of comparing the results of the multivariate analyses.

The only research that did not use the averaged data used the original individual GCM/scenario data presented in section 3.3.4.

2.1.2 Bioclimatic parameters

Both the WorldClim and CIAT datasets include 20 bioclimatic concerns useful in characterizing the biological environment based on the predicted GCM changes (http://ccafs-climate.org/download_down.html). These 20 parameters (Table 1) represent many of the concerns that characterize the living environment in a locality. They are derived directly from the base temperature and precipitation data. Characteristics of the data are well documented at the CIAT website. These are the data types used in these analyses.

Table 1. Bioclimatic categories used for climate change evaluations.

Derived from maximum and minimum temperature (deg C*10):
BIO1 = Annual Mean Temperature
BIO2 = Mean Diurnal Range (Mean of monthly (max temp -min temp))
BIO3 = Isothermality (mean diurnal range/temperature annual range)
BIO4 = Temperature Seasonality (standard deviation *100) (deg C*10)
BIO5 = Max Temperature of Warmest Month
BIO6 = Min Temperature of Coldest Month
BIO7 = Temperature Annual Range (P5-P6)
BIO8 = Mean Temperature of Wettest Quarter
BIO9 = Mean Temperature of Driest Quarter
BIO10 = Mean Temperature of Warmest Quarter
BIO11 = Mean Temperature of Coldest Quarter
Derived from precipitation(in millimeters) :
BIO12 = Annual Precipitation

Derived from maximum and minimum temperature (deg C*10):
BIO13 = Precipitation of Wettest Month
BIO14 = Precipitation of Driest Month
BIO15 = Precipitation Seasonality (Coefficient of Variation)
BIO16 = Precipitation of Wettest Quarter
BIO17 = Precipitation of Driest Quarter
BIO18 = Precipitation of Warmest Quarter
BIO19 = Precipitation of Coldest Quarter
BIO20 = Consecutive Months – the maximum number of consecutive dry months of <100 MM in a year.

2.2 Description of the Maxent application

Maxent is a software program based on the maximum entropy analysis technique. The developers of Maxent currently offer freely downloadable compiled versions of the software for Microsoft Windows users.[3] The software was developed to define the ranges of species based on a multivariate approach.

Entropy in this context is a measure of image information content. Maxent is designed to determine the maximum information content expressed by the data submitted to it. Shannon (1948) described entropy as "a measure of how much 'choice' is involved in the selection of an event." E.T. Jaynes suggested that the best approach for approximating an unknown probability distribution is to ensure that the approximation satisfies any constraints on the unknown distribution; and that, subject to those constraints, the distribution should have maximum entropy (Jaynes 1957).

The maximum entropy approach is theoretically derived from the Second Law of Thermodynamics, which states that in closed systems, processes move toward greater entropy (disorder). As applied to the distribution of a species, the hypothesis is that the sum of the species population behavior will also tend to follow this constraint, and thus result in habitat usage that reflects maximum entropy for it. Since there may be outside influences not included in the input data for a species, the distribution is likely to be larger than the observed delineation. Thus, the maximum entropy approach

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[3] http://www.cs.princeton.edu/~schapire/maxent/.

can be expected to generate a "potential distribution" for each species based on the inputs available.

The Maxent technique develops unbiased probability distribution on the basis of partial knowledge (Phillips 2006). It uses a "presence only" approach, called an *unconditional model*, rather than including data that reflect known-absence sighting (a *conditional model*). In addition, it provides a collection of statistical analysis tools that are highly useful in evaluating the quality of the resulting range map and ancillary outputs. Maxent "takes as input a set of layers or environmental variables (such as elevation, precipitation, etc.), as well as a set of georeferenced occurrence locations, and produces a model of the range of the given species" (Phillips 2008). The idea behind Maxent is to estimate a target probability distribution by finding the probability distribution of maximum entropy (i.e., that is most spread out, or closest to uniform surface), subject to a set of constraints that represent the incomplete information about the target distribution. This is accomplished using a deterministic sequential-update algorithm (Dud´ık et al. 2004). The process iteratively adjusts a weight so as to minimize the resulting regularized log loss. The algorithm is guaranteed to converge to the Maxent probability distribution. Probabilities must sum to 1, so each "raw" probability is typically extremely small. The Maxent software by default presents a "cumulative" probability distribution where the value assigned to a pixel is the sum of the probabilities of that pixel and all other pixels with equal or lower probability, multiplied by 100 to give a percentage.

The advantages of Maxent[4] for the current work include:

- Maps of ranges are generated based on natural, not human-restricted, concerns.
- Efficient deterministic algorithms have been developed that are guaranteed to converge to the optimal (maximum entropy) probability distribution.
- Modelers are allowed to use the original data values.
- Maps have numerical variations based on objective data.
- Statistical evaluations demonstrate the relative importance of each of the inputs.
- Statistical evaluations show species tolerance levels objectively.

[4] A more detailed discussion can be found in Phillips 2006, p 234.

- The selection of specific input layers becomes less important because the output indicates how important each one was to the analysis.
- It is well suited for defining the potential ranges of invasive species, so land managers can find out if their installation is prime habitat for a noxious invasive and prevent or prepare for its appearance.
- Maxent is used by other government agencies.[5]

[5] http://www.fws.gov/Asheville/htmls/Maxent/Maxent.html (Kumar 2009).

3 Modeling RCW Distribution

3.1 Generating the RCW probability distribution

3.1.1 Sample locations

RCW site data acquired from the U.S. Geological Survey Gap Analysis Program (GAP)[6] were adopted as the species sample locations for the following reasons:

- The data are based on a consistent set of objective and stated criteria that are supported by literature and field descriptions.
- GAP digital maps are standard and readily available.
- The data model results show only likely presence.
- The GAP spatial resolution at 30 meters (1 sec=30.9 m) provides more detail than the resolution of the bioclimate data (463.5 m at 32.5 deg north), and is also better than that of other sources.

The limiting spatial resolution for this research, however, was set by the bioclimatic source layers at 0:00:15 deg. This was the standard resolution for all data layers used in the study.

The study area is defined as the maximum extent of the outer limits of the GAP occurrence map. Figure 2 is an example for the RCW on Fort Benning. It illustrates that the RCW locations are really areas of likely habitat. The GAP cell locations were translated into point data for input into the program. This meant that no change in resolution was required for the RCW locations, and also that each bioclimatic cell could have multiple sample locations for RCW.

3.1.2 Bioclimatic data

All 20 bioclimatic layers listed previously in Table 1 were used for the input environmental layers. Some of the other analyses used additional data layers, as described in those sections.

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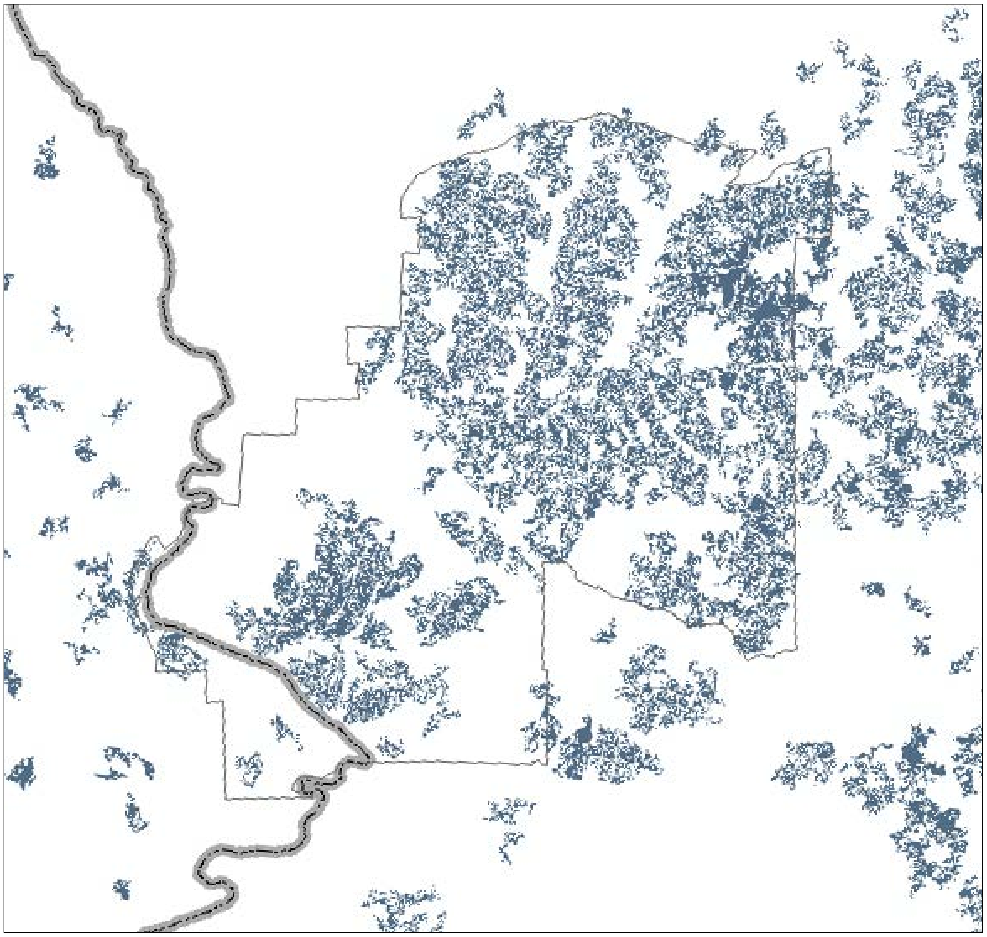
[6] Available from http://gapanalysis.usgs.gov/species/data/download/.

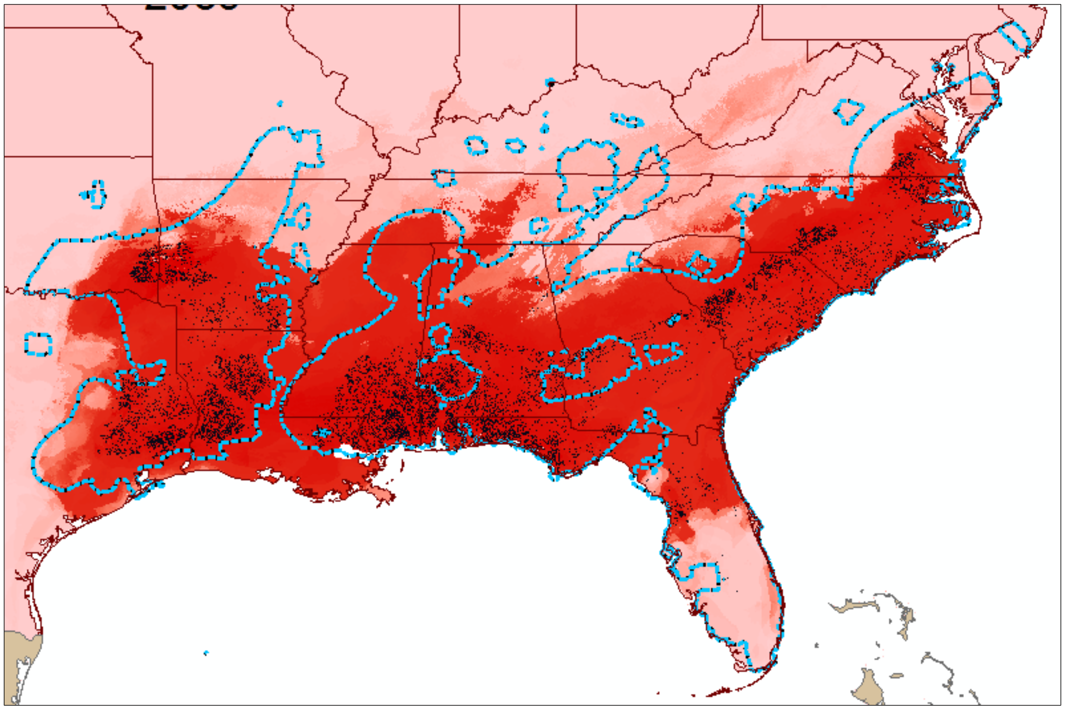
Figure 2. GAP cell locations for likely RCW habitat around Fort Benning.



3.1.3 RCW probability result

The result of the Maxent logistic run with all 20 bioclimatic input layers is shown in Figure 3. This is a probability map, in which probabilities range from 0 to 1. The graphic is the average result of running the RCW model 21 times. Much of the following discussion addresses the summary of the 21 runs. The edge of the deep red areas has a probability of about 0.1. The highest values range near 0.6. One needs to emphasize that this image is generated only on the basis of the 20 bioclimatic concerns already listed. Not included may be other concerns of significance in defining the RCW range. The affects of integrating some of these other concerns into the Maxent analysis is discussed in section 3.2.6.

Figure 3. Probability map of Maxent logistic run with all 20 bioclimatic input layers.



The results are shown in shades of red determined from only the 20 bioclimatic layers and the GAP sites. Outlined in dotted blue is the combination of the two sources for historical distributions. Realize the historic distributions were in no way used to generate the distribution; they represent two independent sources. It is interesting to note that

- the range is extended significantly to the north of the area suggested by the GAP locations
- the Maxent northern boundary better coordinates with the historic range data, in some places almost exactly, than most of the GAP northern limit data
- the Maxent range fills in the questionable holes seen in the historic range data (i.e., the lack of observations does not necessarily mean the absence of species in an area)
- even though the historic range indicates most of Florida should be included, the Maxent range cuts it off north of Tampa.

These observations suggest that Maxent-generated distributions solve problems inherent in distributions found from other sources.

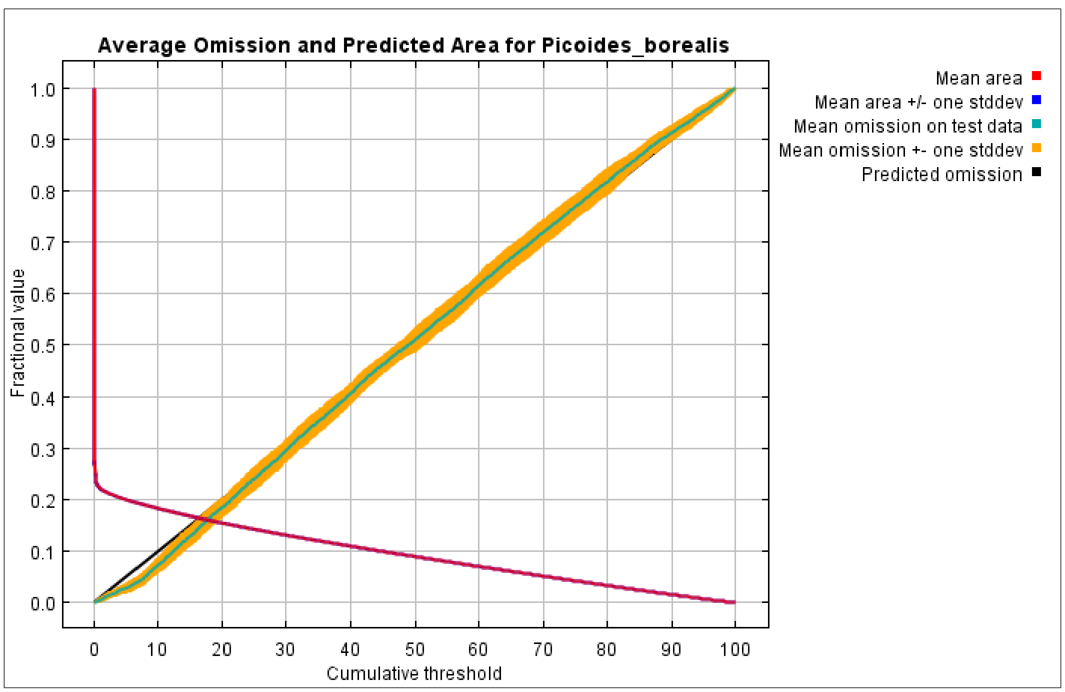
3.2 Evaluation of the RCW model

3.2.1 Statistical assessment of results

As previously stated, the advantage of using Maxent is that it generates several statistical evaluations of the quality of its output. Here we review some of those assessments for the RCW model.

Figure 4 shows the omission rate and predicted area as a function of the cumulative threshold. During the modeling, 80% of the GAP sites were used to train the model and 20% were set aside to serve as the testing data, which Maxent would use to check for correct fit with the model output. The lack of correctness, or omission rate — the fraction of the test localities that fall into pixels not predicted as suitable — is calculated both on the training records (blue line), and on the test records (pink). If the model is good, the omission rate should be close to the predicted omission (black, which is nearly covered by the salmon area). In this model the lines are very similar, meaning the model is very good.

Figure 4. RCW omission rate and predicted area as a function of the cumulative threshold.

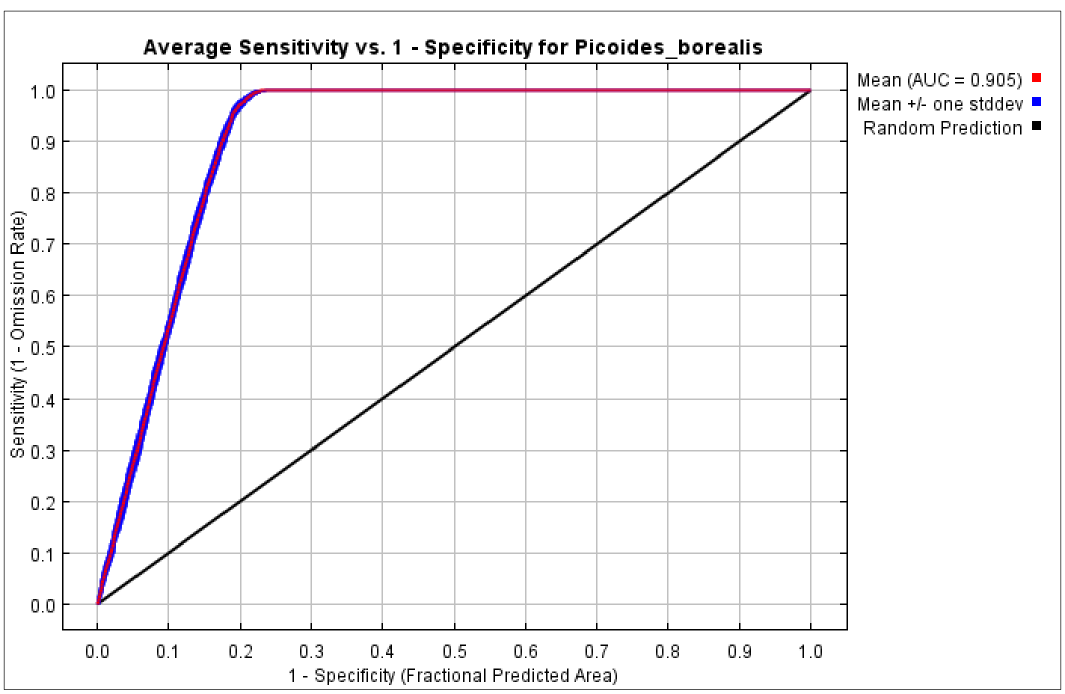


The salmon color indicates the standard deviation of all 21 runs in the mean omission. It is tight about the mean, so there is not much variation. If the training and test lines lay well below the predicted line, that would

imply the two were not independent, meaning they could be spatially auto correlated. In this case, according to Maxent, they are not. The fraction of background pixels predicted to be RCW habitat that is actually not (the area below the red line) drops immediately to a low value and stays low, showing the model and background areas are not confused.

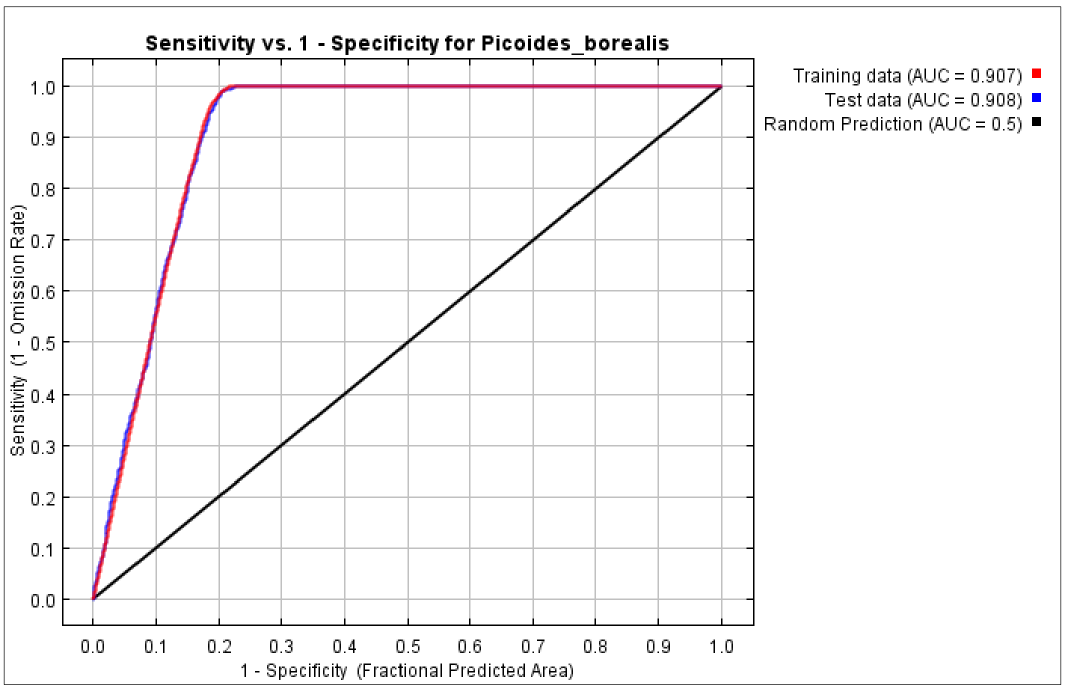
In Figure 5 the receiver operating curves (ROCs) for both training and test data are shown. (An ROC is a plot of sensitivity versus specificity, or randomness; its name derives from its original use in the field of radar technology.) The black line shown in the ROC represents what one would expect if the model resulted in a useless test—one that has no discriminatory power. The size of the area between the black line and the red lines in the ROC reflects the ability of a test to discriminate between presence and non-presence of RCW across the range of potential cutoffs. The blue area shows one standard deviation from the mean in all 21 model runs. There is little variance in this summary model. The area under the curve (AUC) provides a single measure of model performance independent of any particular choice of threshold. The AUC can be interpreted as the probability that a random positive instance and a random negative instance are correctly ordered by the classifier. The larger the AUC, the better the model has performed. The RCW value of 0.905 is very high.

Figure 5. ROC for both RCW model training and test data.



If we examine the ROCs from some of the individual runs (Figure 6 is an example), we can obtain additional information about our model. The black line shows the plot one would expect if this model were no better than random (AUC =0.5). The red (training) line shows the fit of the model to the training data (AUC = 0.907). The blue (testing) line indicates the fit of the model to the testing data, and is the real test of the model's predictive power. The further toward the top-left portion of the graph that the blue line is, the better the model is at predicting the presence of RCW contained in the test sample of the data. With a test sample AUC of 0.908, this single run of the RCW model predicts distribution extremely well.

Figure 6. ROC from an individual run for the Maxent RCW model.



As noted above, the data were split into two model-training and -testing partitions. It is normal for the training (red) line to show a higher AUC than the testing (blue) line, but in the current case, the two are almost the same. If the blue line (the test line) fell below the black line, that would indicate the model performs worse than a random model would. If we used the same data for training and for testing, then the red and blue lines would be identical. We did not, but those curves are extremely similar. It is important to note that AUC values tend to be higher for species with narrow ranges, relative to the study area described by the environmental data. This does not necessarily mean that the models are better; instead, this behavior is an artifact of the AUC statistic. The input data covers all of

CONUS, so a range covering all of the southeastern United States is not large, but neither is it narrow. Therefore, this caveat only marginally applies to this particular test.

Because test data were set aside, the Maxent program automatically calculated the statistical significance of the prediction. Table 2 shows some metrics for the same single RCW model as above (Figure 6) under a series of differing threshold levels. The table displays a P-value test, showing only whether the habitat is suitable or unsuitable. To do a test, a decision must be made as to what threshold value constitutes a suitable habitat (i.e., what probability value is the minimum value for suitable habitat). There is no rule for these thresholds, so to be conservative, a several different tests were run with a variety of reasonable thresholds. The more tests the model passes, the more confident we can be that it is a valid model.

Table 2. Maxent tests for the viability of the RCW model.

Cumulative Threshold	Logistic Threshold	Test Description	Fractional Predicted Area	Training Omission Rate	Test Omission Rate	P-Value
1.000	0.182	Fixed cumulative value 1	0.222	0.002	0.004	0E0
5.000	0.339	Fixed cumulative value 5	0.199	0.019	0.023	0E0
10.000	0.411	Fixed cumulative value 10	0.181	0.060	0.072	0E0
0.148	0.009	Minimum training presence	0.258	0.000	0.000	0E0
13.399	0.433	10 percentile training presence	0.171	0.100	0.109	0E0
18.224	0.462	Equal training sensitivity and specificity	0.158	0.158	0.162	0E0
3.327	0.299	Maximum training sensitivity plus specificity	0.207	0.009	0.010	0E0
17.458	0.458	Equal test sensitivity and specificity	0.160	0.149	0.160	0E0
3.505	0.302	Maximum test sensitivity plus specificity	0.206	0.010	0.010	0E0
1.179	0.209	Equate entropy of threshold and original distributions	0.220	0.002	0.004	0E0

For example, for the 10 Percentile Training Presence test (the fifth test under Test Description in Table 2), a 10% minimum threshold was used to define the minimum probability of suitable habitat. If the data we are using is likely to contain errors, then this threshold limits the effect of those errors in evaluating the model. Therefore, we define suitable habitat to include 90% of the data we used to develop the model. If we were more certain of the quality of the data, we may have used a 5% threshold or one of

the other more stringent tests. Each threshold (cumulative and logistic) was used to obtain a binary (presence vs absence) test for the species. Output column headings (Table 2) are:

- Thresholds (Cumulative and Logistic) used for the test
- Test Name
- Fractional Predicted Area, the proportion of total area predicted to contain the species
- Training Omission Rate, the rate of failure to predict a species' occurrence where it is known to occur with the training data.
- Test Omission Rate, the rate of failure to predict a species' occurrence where it is known to occur with the test data
- P-values, the probability for each threshold that the model's predictions are random using a one-tailed binomial test.

Statistical literature describes each test in detail; here Maxent applies some common tests to the RCW model.

The tests in Table 2 are one-sided probability (P-values) for the null hypothesis test, "Points are predicted no better than by a random prediction with the same fractional predicted area." All p-values are vanishingly small, so the hypothesis "the RCW model is close to random" is false under all tests.

3.2.2 Analysis of variable contributions

While the RCW model is being trained, in each iteration of the 21 runs Maxent keeps track of which environmental variables are making the greatest contribution to the model. The results averaged from all 21 runs are shown in Table 3. As each step of the Maxent algorithm incrementally changes the model, Maxent assigns the increased (or decreased) improvement amount to the environmental variable(s) that the feature depends on. Converting this total value to percentages at the end of the training process, Maxent generates the Percent Contribution column. For each environmental variable in turn, the value of that variable on training presence and background data are randomly permuted. The model is reevaluated on the permuted data (another graph like Figure 6 is generated), and the resulting drop in training AUC is shown in the table (normalized to percentages) as the Permutation Importance column. Higher permutation values show higher potential for changes in the percent contribution column. In this case, we see that there is some potential varia-

tion, but those in the top ranks (the top three or four) will remain the most important in any case.

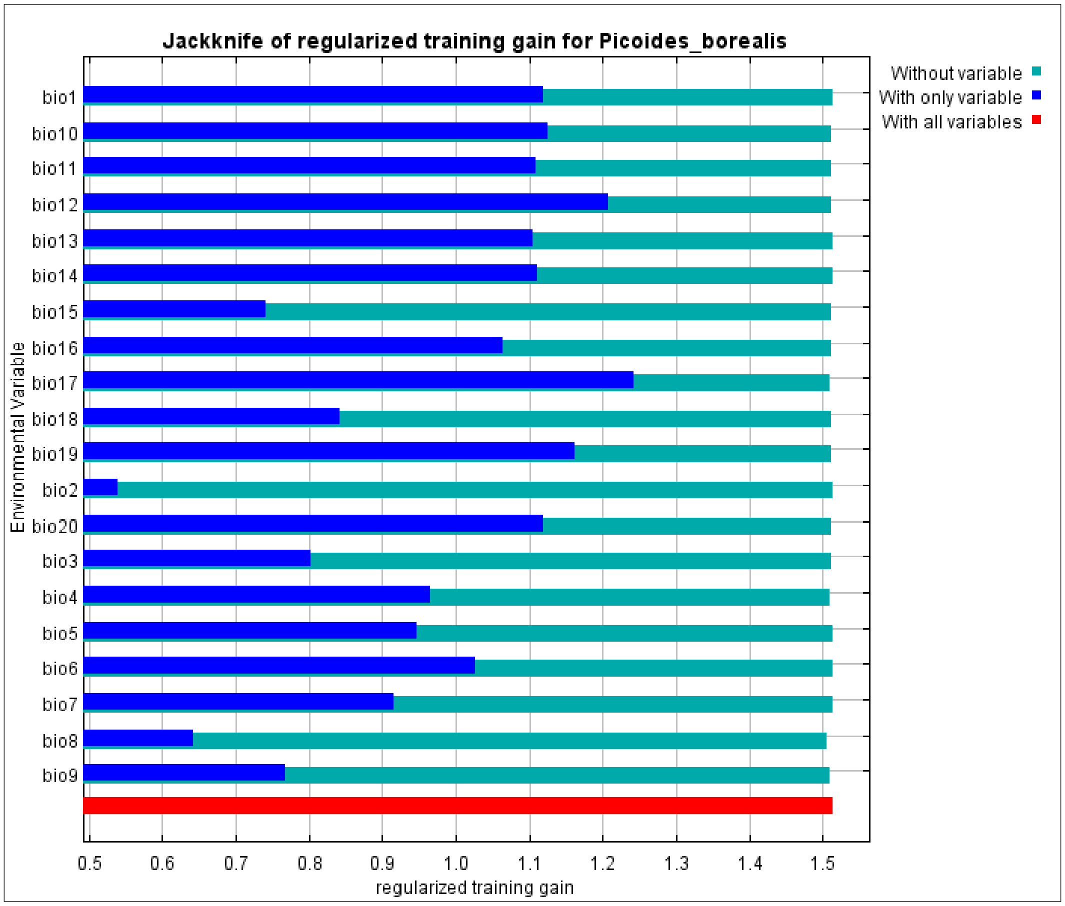
Table 3. Input variable importance and permutation for the RCW model.

Variable	Percent Contribution	Permutation Importance
bio17	38.4	18.2
bio12	21	5
bio10	14.5	7.1
bio1	12.5	3.5
bio6	3.2	3.3
bio4	2.2	9.8
bio11	1.7	3.8
bio14	1.6	4.2
bio8	1.4	5.8
bio3	0.9	7
bio13	0.7	6.7
bio9	0.6	8
bio20	0.5	0.5
bio2	0.3	2.4
bio19	0.2	1.6
bio18	0.2	7.9
bio15	0.1	1.6
bio7	0.1	0.8
bio5	0.1	1.4
bio16	0	1.3

An alternate estimate of which variables are most important in the model can be determined by a "jackknife" analysis. For a jackknife analysis, during a program run for a single analysis of the 21 runs, a number of submodels are created. Each layer variable is excluded in turn so that a model is created with the remaining variables. Then a model is created using each variable in isolation. Finally, a model is created using all variables, as before. The jackknife analysis produces three bar charts, as described below.

Figure 7 shows the gains in viability based on the "training" locations. The red line at the bottom of the graph shows the complete RCW model with all variables for one of the 21 runs. The environmental variable with highest gain when used in isolation (the blue bar) is Bio17, Precipitation of Driest Quarter, which therefore appears to have the most useful information by itself.

Figure 7. Jackknife test gain in viability based on the “training” locations.

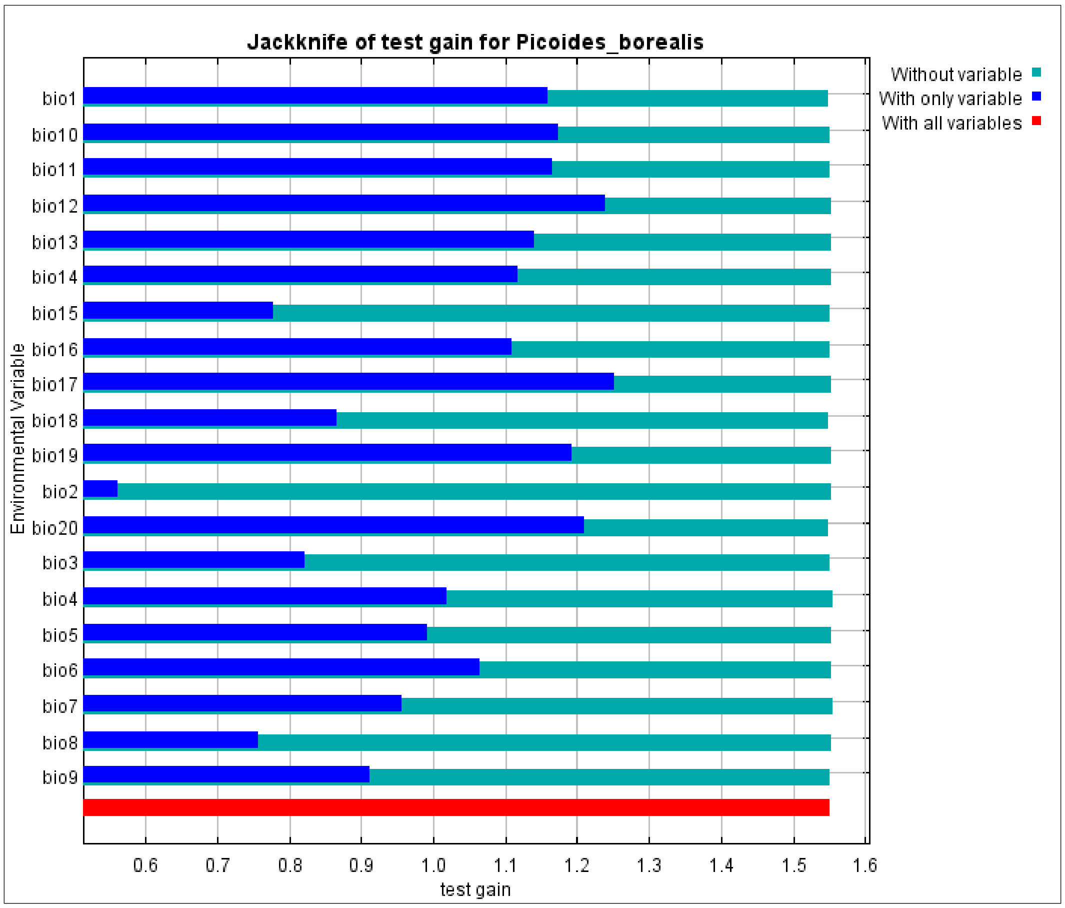


In this particular run, this is followed by Bio12, Annual Precipitation. Bio17 and Bio12 are both in the top four in Table 3. By contrast, bio2 (Mean Diurnal Range) makes almost no contribution in gain. It can be dropped from the analysis with little consequence. In general, the “with only variable” analysis varies among the layers, so making a model with only a single input can be important. The environmental variable that decreases the gain the most when it is omitted (the green bar) is bio8, Mean Temperature of Wettest Quarter, which therefore appears to have the most information that isn’t present in the other variables. However, it appears that no variable contains a substantial amount of useful information that is not already contained in the other variables, because omitting each variable in turn did not decrease the training gain considerably. In general, the “without variable” analysis stays about the same across the board, so eliminating one variable really is not important. In fact, for all three jackknife charts (Figure 7 – Figure 9), the “without variable” stays near the model maximum value (the red bar). This means that dropping any one variable

is not important; the information lost from a dropped variable is contained among the others.

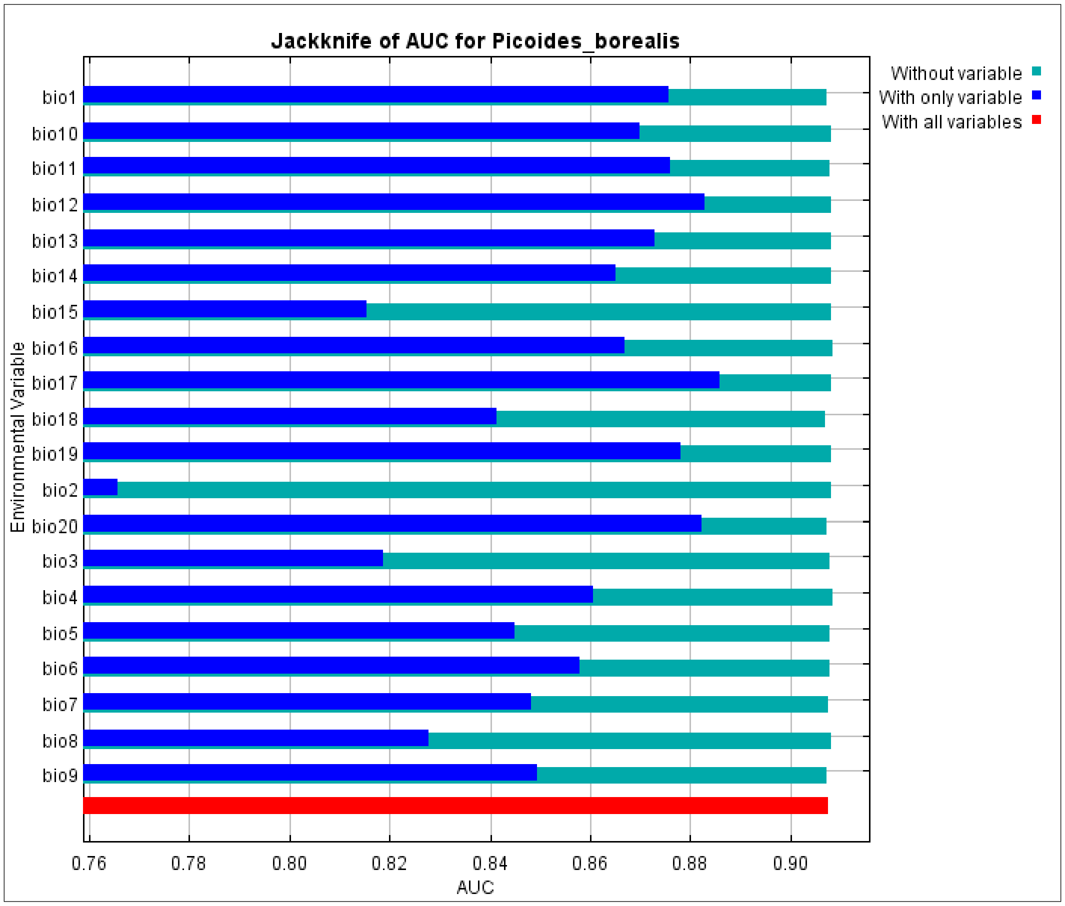
Figure 8 shows the gains based on the “testing” locations. Bio17 and Bio12 remain most important and bio2 the least important among the “with only” variables. Among the “without” variables there is little change in the bar lengths once again, so they have little effect.

Figure 8. Jackknife test gain in viability based on the “testing” locations.



Finally, Figure 9 shows the same jackknife test using the AUC on test data. The AUC plot shows once again that bio17 is the most effective single variable for predicting the distribution of the occurrence data that were set aside for testing, when predictive performance is measured using AUC. Bio20 and Bio12 follow. It is not surprising that bio20 rates highly because consecutive dry months is very similar to Precipitation of Driest Quarter. Bio2–Mean Diurnal Range, was the least effective for prediction.

Figure 9. Jackknife test using AUC on test data.



This tells us that monthly precipitation variables are helping Maxent to obtain a good fit to the model-training data, but the Precipitation of Driest Quarter variable generalizes better, giving comparatively better results on the set-aside test data. Phrased differently, models made with the Precipitation of Driest Quarter variables appear to be less transferable. This is important if the goal is to transfer the model, for example by applying the model to future climate variables in order to estimate its future distribution under climate change. It makes sense that Precipitation of Driest Quarter values are less transferable; likely suitable conditions for RCW will depend not on precise rainfall values, but on the dry month limits.

3.2.3 Model ancillary outputs

The single-concern marginal response curves in Figure 10 show how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes as each environmental variable is changed while keeping all others at their average sample value.

Figure 10. How environmental variables each singly affect the Maxent prediction.

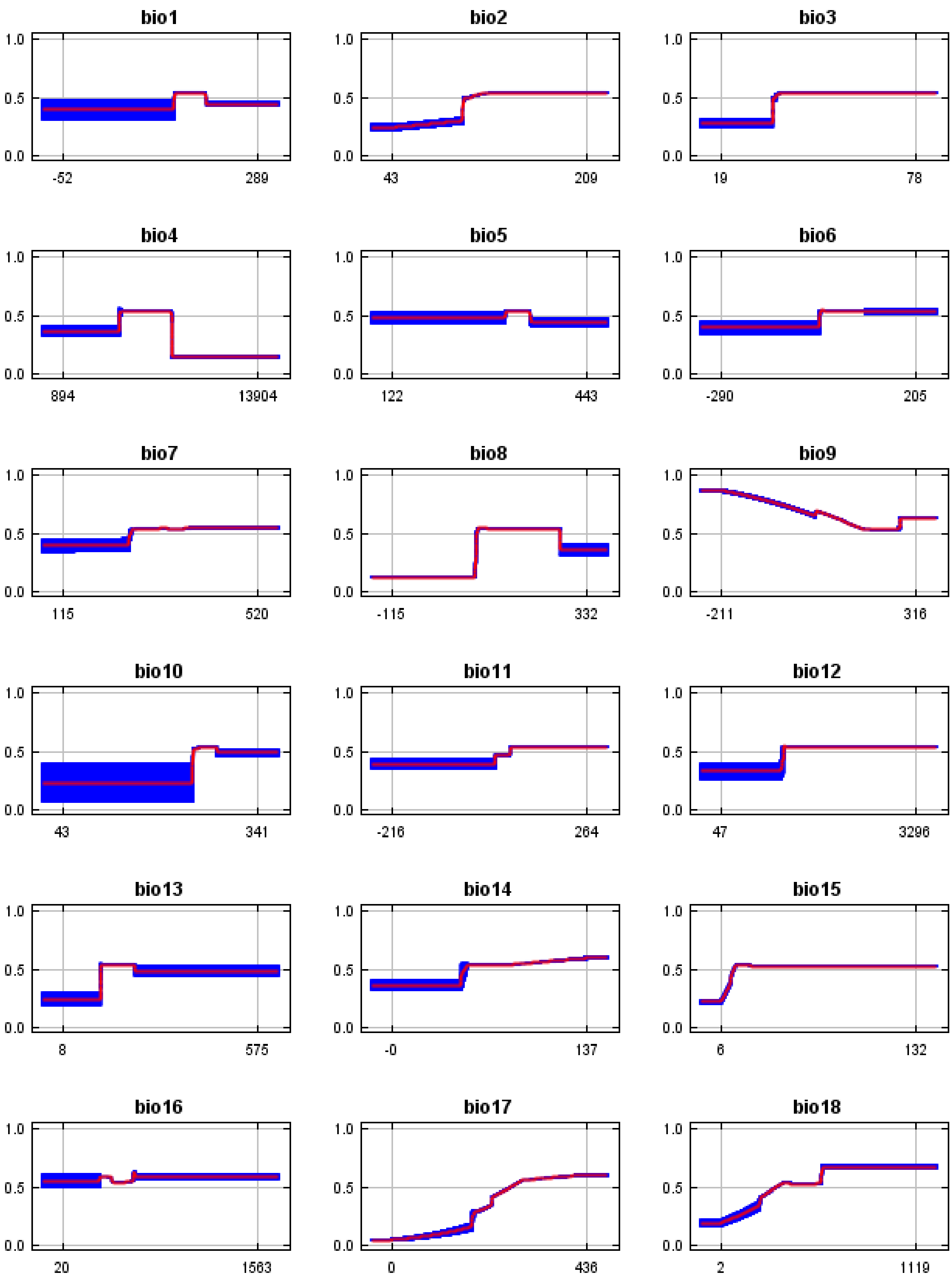
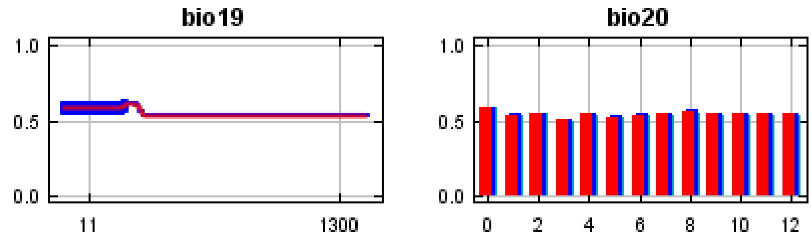


Figure 10 (concluded).



The value shown on the y-axis is predicted probability of suitable conditions, as given by the logistic output format. A value near 1 means the species reacts well to this condition. A value near 0.5 means this condition is not materially limiting or advantageous to the species. A value near zero means it cannot tolerate this condition. In the graph for bio1 (Mean Annual Temperature) there is no significance indicated over the range from -5.4–14 °C (x-axis values in the bio1 chart are temperature, in degrees Celsius, multiplied by 10). From 14–20 °C, there is a small positive benefit. There is negative bias for the RCW (about 0.44) for Mean Annual Temperature values higher than 20 °C, but not a bias so great that it would preclude the species from existing. If the red line goes to near zero, then that is a climatic range that is inappropriate for the species. The blue area shows one standard deviation from the mean for all 21 model runs. For bio1 the blue areas are wide, so for mean annual temperature there is a good deal of variation in what the RCW will tolerate.

If the variables are strongly correlated, the curves in Figure 10 may be hard to interpret. Figure 10 curves show the marginal effect of changing just one variable. However the RCW model may take advantage of sets of variables changing together. In Figure 11 below the Maxent model was created using the indicated variable and statistically related other variables (correlated marginal response curves). That is, these plots reflect the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and other associated variables. If there are strong correlations between variables, Figure 11 is easier than Figure 10 to interpret. Comparing Figure 10 and Figure 11 below, thresholds almost always coordinate between the two graph pairs, but the thresholds are more evident in Figure 11. Also note that the charts in Figure 11 exhibit much less variance in one standard deviation (indicated by the blue areas) than in the previous figure, so the information they represent are more stable.

Figure 11. Correlated marginal response curves for the RCW.

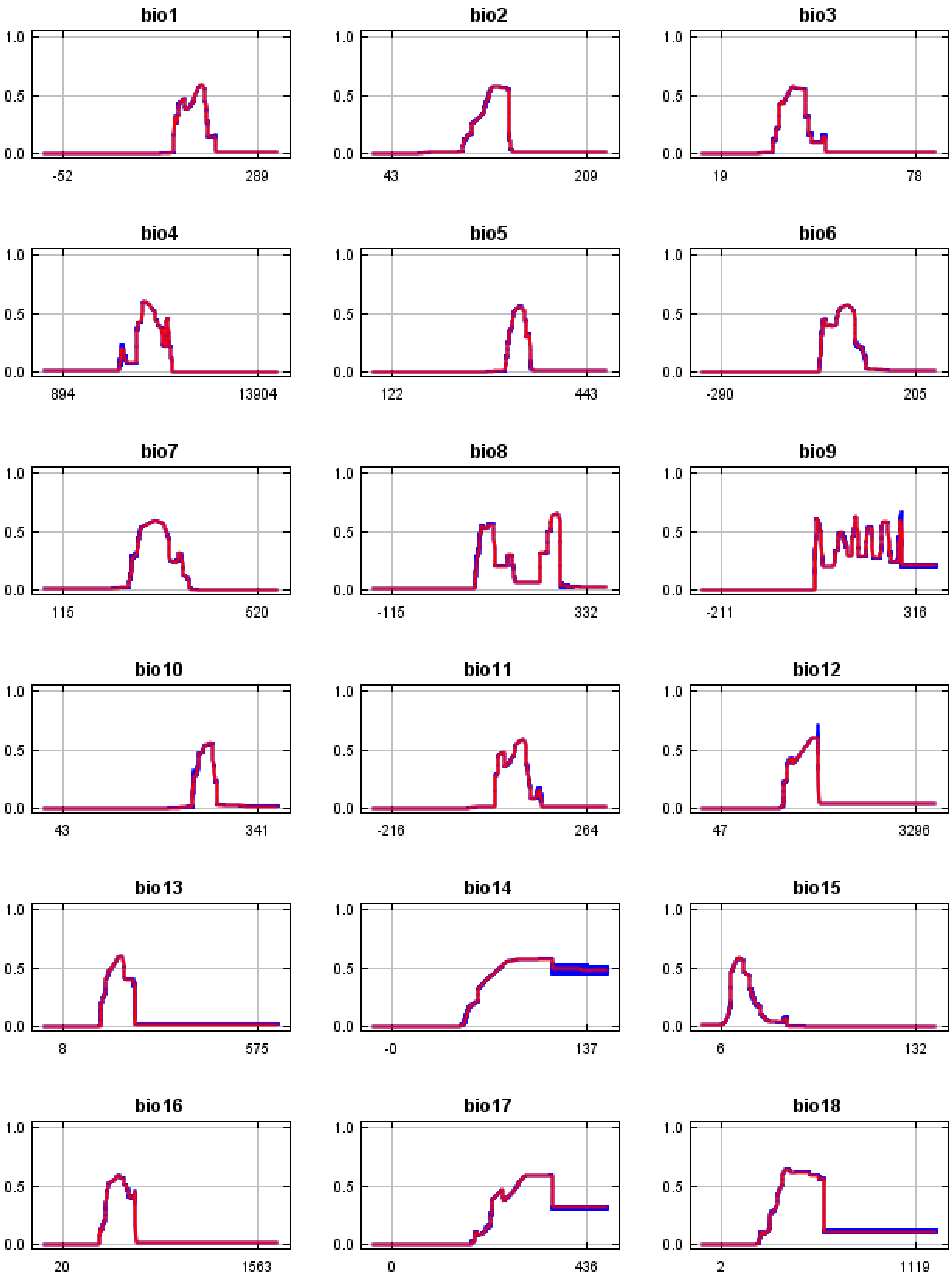
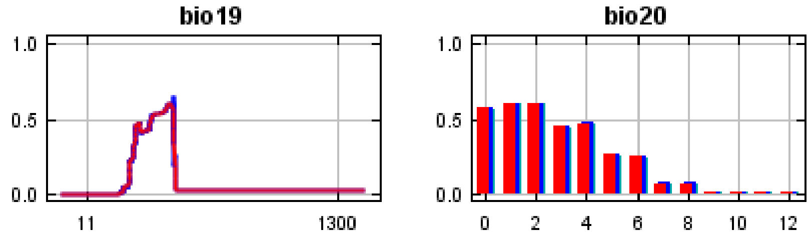
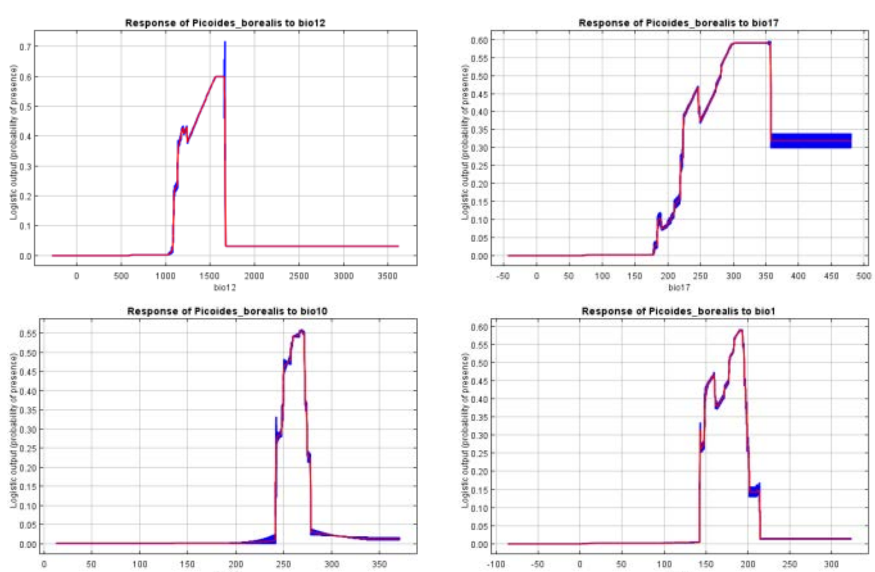


Figure 11 (concluded).



When comparing the charts in Figure 10Figure 10 and Figure 11, the outlines of two coordinating profiles are similar, but they differ because different feature types allow different possible shapes of response curves. The plotted exponent in a Maxent model is a sum of features, and a sum of threshold features is always a step function, so the logistic output is also a step function (as are the raw and cumulative outputs), as shown in the marginal response curves of Figure 10. In comparison, when hinge features are applied to the response curves, the lines in the charts become smoother. (Hinge features are graph locations where occurrence data begin to become common [at least 15 samples], i.e., the lower and upper thresholds.) Some lines are curved, especially toward the extreme values of the variable, because the logistic output applies a sigmoid function to the Maxent exponent. Using all classes together—the default, given enough samples—allows many complex responses to be accurately modeled. Figure 12 shows the four charts listed as the highest-percent contribution from Table 3 in more detail.

Figure 12. Four charts listed as the highest percent contribution inputs to the RCW model.



3.2.4 Thresholds

Now it is possible to combine the information from the response curves (Figure 11) and Table 3 to generate a table of how important each of the bioclimatic layers is to the RCW and what its thresholds are (Table 4).

Table 4. Bioclimatic thresholds for the occurrence of the RCW.

Bio Num	Bioclimatic Concern	Lower Threshold	Severity	Occurs below Threshold?	Upper Threshold	Severity	Occurs above Threshold	% Importance in Model
BIO17	Precipitation of Driest Quarter (cm)	18.0	Moderate High	No	36.0	Extreme	Yes	38.4
BIO12	Annual Precipitation (in centimeters)	110.0	Extreme	No	170.0	Extreme	No	21
BIO10	Mean Temperature of Warmest Quarter (deg C)	24.0	Extreme	No	27.8	Extreme	No	14.5
BIO1	Annual Mean Temperature (deg C)	14.0	Extreme	No	22.0	Very High	No	12.5
BIO6	Min Temperature of Coldest Month (deg C)	-4.5	Extreme	No	8.0	Very High	No	3.2
BIO4	Temperature Seasonality (standard deviation*10)	4500.0	High	No	8100.0	High	No	2.2
BIO11	Mean Temperature of Coldest Quarter (deg C)	4.0	Extreme	No	15.0	High	No	1.7
BIO14	Precipitation of Driest Month (cm)	5.0	Moderate High	No	11.3	Extreme	Yes	1.6
BIO8	Mean Temperature of Wettest Quarter (deg C)	7.5	Strange	No	27.0	Strange	Barely	1.4
BIO3	Isothermality (mean diurnal range/temperature annual range)	34.0	Very High	No	51.0	High	No	0.9
BIO13	Precipitation of Wettest Month (cm)	11.0	Very High	No	22.0	Extreme	No	0.7
BIO9	Mean Temperature of Driest Quarter (deg C)	4.5	Extreme	No	28.0	Strange	Yes	0.6
BIO20	Maximum number of consecutive dry months (<100 MM/year)	None	-	-	6.0	Low	Yes	0.5
BIO2	Mean Diurnal Range (Mean of monthly (max temp -min temp)) (deg C)	10.4	Very High	No	14.3	Extreme	No	0.3
BIO19	Precipitation of Coldest Quarter (cm)	21.0	Very High	No	47.0	Extreme	No	0.2
BIO18	Precipitation of Warmest Quarter (cm)	21.0	Moderate High	No	60.0	Extreme	Yes	0.2
BIO15	Precipitation Seasonality (Coefficient of Variation)	7.0	Extreme	No	50.0	Moderate	No	0.1
BIO7	Temperature Annual Range (P5-P6) (deg C)	25.0	Very High	No	37.5	Very High	No	0.1
BIO5	Max Temperature of Warmest Month (deg C)	31.0	Extreme	No	35.0	Extreme	No	0.1
BIO16	Precipitation of Wettest Quarter (cm)	31.0	Very High	No	60.0	Extreme	No	0

For the RCW, the controlling bioclimatic factors (60% contribution to the RCW model) are the precipitation of driest quarter (winter) and the annual precipitation. For the precipitation of driest quarter, the lower threshold

is 18 cm of rain, but it is not a cutoff limit. The upper limit of 36 cm is a sharp limit, but above it the RCW will survive. Annual precipitation is very important and severely limiting. For the mean annual precipitation, the lower threshold is 110 cm, a cutoff limit below which the RCW does not occur. The upper limit of 170 cm is also a sharp limit, above which the RCW will not survive. Annual precipitation, therefore, is more important precipitation of the driest quarter in limiting the RCW potential occurrence. Mean temperature of the warmest quarter is the next-most-important concern (14.5% contribution to the RCW model) followed by annual mean temperature (12.5% contribution). Together these four variables explain 86% of the RCW distribution.

These results do not reflect weather events, particularly highly unusual weather occurrences. However these data suggest that when unusual weather events occur, the RCW is resilient to its most important climatic concerns, but the RCWs ability to survive is most affected by extreme low or high temperatures during summer.

3.2.5 Using fewer bioclimatic inputs

If just four bioclimatic factors explain 86% of the model (Table 5), then how different would the model be using only those four factors? A corollary question is, “How significant is the remaining 14% of the model to the output?”

Table 5. Most important four inputs of the 20 bioclimatic factors in the previous RCW model.

Bio17_PrecipDryQtr	38.4%
Bio12_AnnPrecip	21%
Bio10_MeanTempWarmQtr	14.5%
Bio1_PreWarmQtr	12.5 %

To explore these questions, the model was run using only the top four factors. The result can be seen in Figure 13, which includes a blue line that indicates the RCW probability produced by modeling all 20 bioclimatic factors. The output differences between the original model and the four-factor model are shown in Figure 14, where blue-green areas show increases in distribution and red areas show decreases when modeling only the four most-important bioclimatic factors.

Figure 13. Maxent RCW probability using only the four most important inputs (red) compared with the distribution using all 20 factors (blue dotted line).

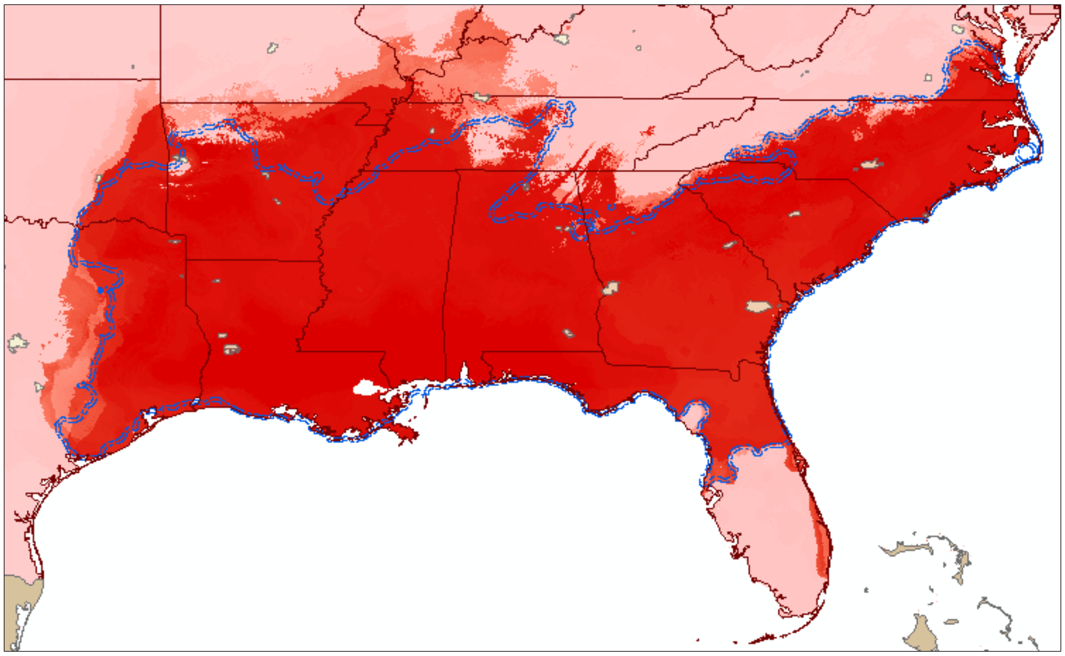
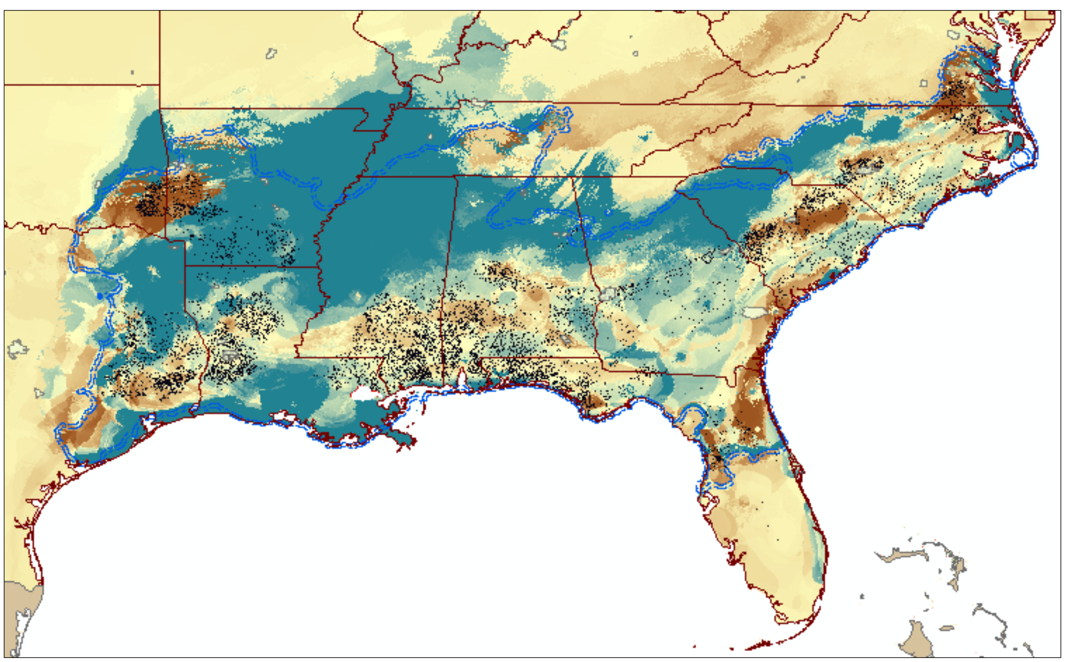


Figure 14. Regional distribution changes, with blue-green showing increases, red showing decreases, and black dots showing GAP sample data.



The result is similar to the original 20 bioclimatic model (blue double dashed line), showing that these four are truly important primary inputs. The use of only four factors seems to make the probability distribution somewhat less restrictive, particularly along the Mississippi River area in

Arkansas and Tennessee. In Figure 14, greater red means areas have contracted from the original distribution, darker blue-green means the areas are more definitely RCW territory, and yellow means no change). The change values suggested by the figure (a maximum of 0.35 for the decreased areas while the increased areas exhibit a much larger 0.55 maximum change out of a potential range of 1.2). The probability distribution using only four variables is similar to the original, but less restrictive. The analysis of variable contribution is also similar (Table 6). In terms of the relative importance of each of the bioclimatic factors, precipitation of the driest quarter remains primary (as well as in all the jackknife tests) while mean temperature of the warmest quarter becomes more important than annual precipitation by 8.1 percent.

Table 6. New importance distribution for just the four bioclimatic concerns.

Variable	Percent contribution	Permutation importance
Bio17_PrecipDryQtr	46.8	54.3
Bio10_MeanTempWarmQtr	24.3	15
Bio12_AnnPrecip	16.2	10.1
Bio1_PreWarmQtr	12.7	20.6

Another sensitivity test of the Maxent input is to determine what happens when the four least-important inputs (Table 7) are used in a Maxent run.

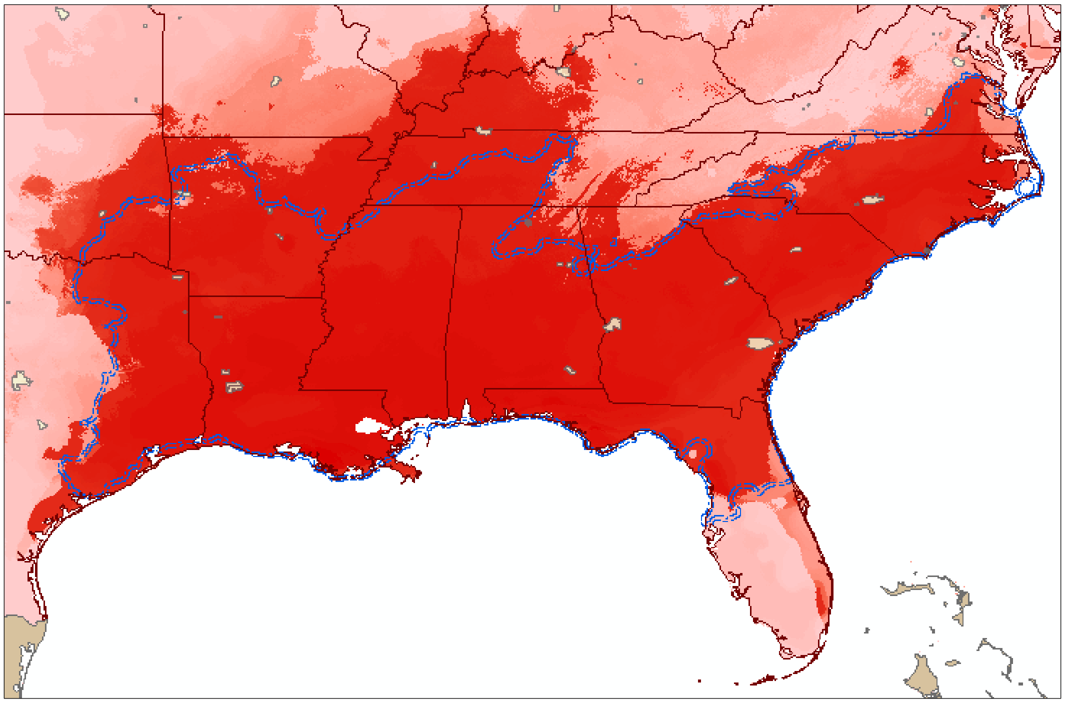
Table 7. Least important four inputs of the 20 bioclimatic concerns in the original RCW model.

Variable	Percent contribution	Permutation importance
Bio15 Precipitation Seasonality	0.1	1.6
Bio7 Temperature annual Range	0.1	0.8
Bio5 Maximum Temperature of the Warmest Month	0.1	1.4
Bio16 Precipitation of Wettest Quarter	0	1.3

Figure 15 shows the results of defining RCW habitat probability using only these four least-important bioclimatic concerns. While using the top-four inputs resulted in a probability distribution that was less restrictive compared to using all 20 bioclimatic concerns, using the bottom-four inputs resulted in a probability distribution that was surprisingly similar but even

less restrictive, particularly on the northern boundary in the central United States.

Figure 15. Maxent RCW probability distribution using only the four least-important inputs (red) compared with using all 20 bioclimatic factors (blue dotted line).



There is some relation between the top-four and bottom-four variables. The most important variable in this model was bio16, precipitation of wettest quarter, which is roughly equivalent to bio1 precipitation of the warmest quarter in the original model for the southeastern United States. The second-most-important factor was bio5, maximum temperature of the warmest month, which is roughly equivalent to bio10, mean temperature of the warmest quarter in the original model. Looking back at the jackknife tests (Figure 7 – Figure 9), it can be seen that none of these four least-important factors predicts the model well on its own, as indicted by the length of the blue bars.

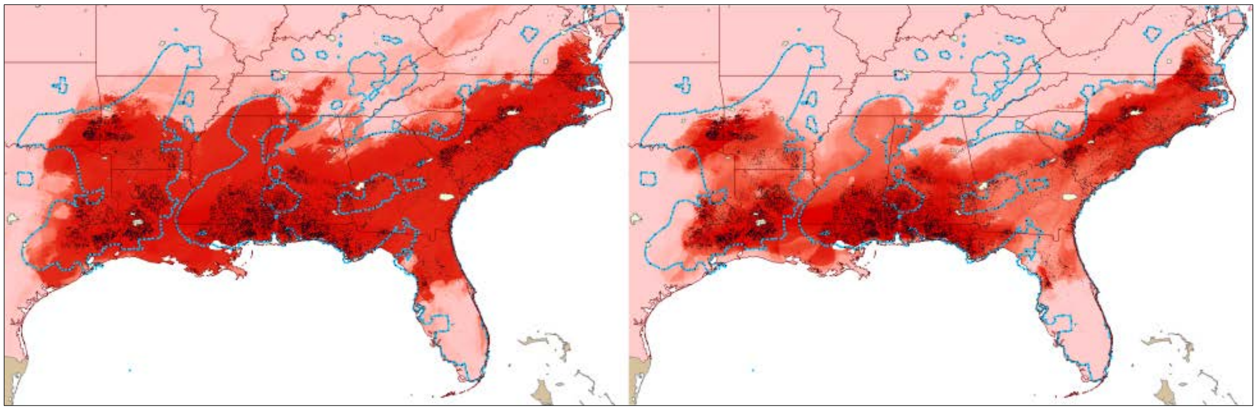
The significant observation for this section is that whatever the climatic inputs, the Maxent spatial probability distribution is similar in all cases (using all 20 inputs, or just the top four, or just the bottom four). Even the use of poorly descriptive environmental inputs will produce a good approximation of the RCW habitat probability distribution, and the more data available, the tighter the probability extent will be.

3.2.6 Refining potential RCW habitat with additional input layers

It has often been pointed out that the distribution of RCW is largely coincident with Longleaf and Shortleaf Pines (Conner 1991, Department of Defense 1991). These tree species are not found along the Mississippi valley, but the Maxent model shows that area to be good RCW habitat based solely on bioclimatic considerations. From the probability distributions presented so far, the southern Mississippi valley would appear to be fully suitable for RCW nesting based on bioclimatic factors. But the RCW rarely inhabits the valley because of the absence of these trees. Tree species known to be important to RCW nesting activities do not grow in the Mississippi Valley, but model output shown up to this point does not reflect that because it does not account for critical flora. An interesting question is whether the model as configured thus far did capture that fact to any extent.

Up to this point, the results of the model runs have been presented in a single color to ensure compatibility between different analyses. However, the color contrast for the output can be increased to facilitate closer examination of the results. Figure 16 shows the standard color table used up to this point on the left, and a higher-contrast color table on the right. Both versions show the RCW sample input points as black dots and the traditional range definitions within the dotted blue lines. The darker red areas (higher probabilities) coordinate more closely with the GAP sample points. Using the higher-contrast color table, the decreased quality of RCW habitat becomes apparent along the Mississippi lowlands, the Texas-Louisiana Gulf coast, and a section centered on Fort Stewart (the small polygon in southeastern Georgia), trending southwest to northeast. Thus, Maxent recognized what is already known in the discipline: poorer RCW habitat potential exists along the Mississippi lowlands.

Figure 16. Comparison of model results when presented in standard color table (left) and higher-contrast color table (right).



It seems reasonable to suppose that the model results might be significantly improved if a data layer were included to account for landform characteristics. A survey of data sets accessible on the web found that a categorized open-source landform digital map is not available. (The USGS landform map[7] is an image, not a categorized landform map.) Nevertheless, a similar theme to landform would be land physical geography, or *physiography*. A digital version of the classic Physiographic Regions of the United States[8] map was acquired and submitted as a Maxent input layer.

In the new analysis of variable contributions, physiography ranked fifth in importance, contributing 3.5% to the overall model. Even at that level of importance, physiography had a significant influence on model results. In the jackknife test, physiographic region was the environmental variable with highest gain when used in isolation, therefore apparently having the most useful information by itself. It is also the environmental variable that most decreases the gain when omitted, therefore apparently having the most information that isn't accounted for by the other variables. This might be expected since all the other variables are bioclimatic factors.

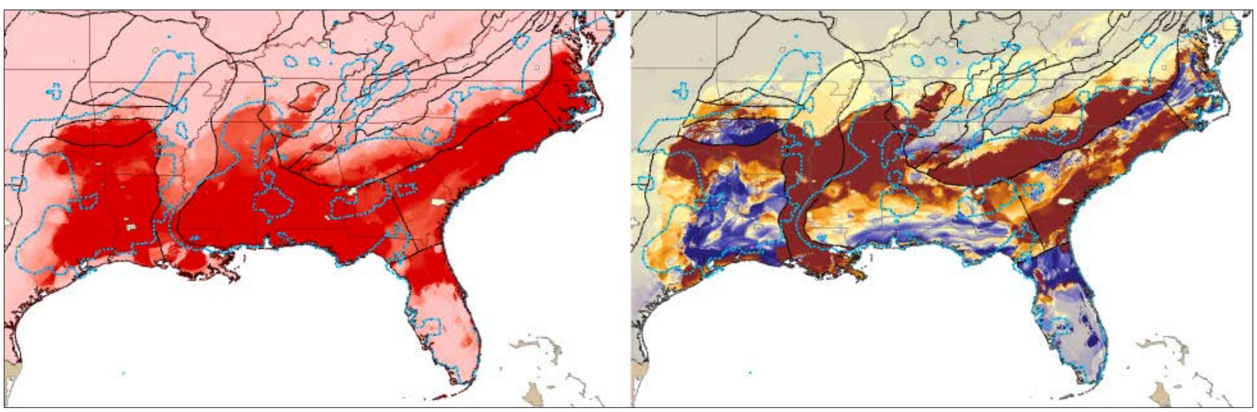
Figure 17 shows the new map on the left and the difference between the new map and the original distribution on the right, where increased probabilities are bluer and decreased are redder. It can be seen that the increases and decreases are often closely determined by the edges of physiographic regions (black lines) categories (e.g. central Louisiana along

[7] http://pubs.usgs.gov/imap/i2206/.

[8] Fenneman, Nevin M. (January 1917). "Physiographic Subdivision of the United States". Proceedings of the National Academy of Sciences of the United States of America 3 (1): 17–22. OCLC 43473694. PMC 1091163. PMID 16586678.

the Mississippi lowland edge). There is a well defined decrease in probability of RCW occurrence along the Mississippi lowland (which is what we were expecting) while there are also occurrence restrictions in the Appalachian region that pulls the preferred habitat further south of the traditional boundaries (blue dotted line). Now with the inclusion of physiography, the restrictions along the Appalachian region more closely reflect the distribution of the GAP input sample points. Similarly there is a noticeable decrease in suitable habitat centered on Fort Stewart, GA and trending southwest to northeast reflecting a dearth in the presence of input sample points. As a weighted sum (cell count * probability value) there is twice as much decreased RCW habitat as increased compared to the original bioclimate factors only map. Adding the physiography layer to the analysis enhances the influence of both the sample data as well as the physiography.

Figure 17. New map (left) showing physiographic regions (black lines) and comparison map (right) showing differences with the original distribution (increased probabilities are bluer, decreased are redder).



The potential RCW range is also impacted by urban expansion and change of land use to agriculture. Such data are time-dependent, reflecting the impact of humans over time. The Maxent probability output was examined to determine whether that change is reflected in the results.

The USGS GAP data includes a land-cover map[9]. That map (Figure 18) clearly shows distinctive lowland vegetation along the Mississippi Rive valley. The map, detailed to the "Ecosystem Land Use" level, was used as one

[9] http://gapanalysis.usgs.gov/gaplandcover/data/download/.

of the submission layers in the RCW Maxent model to see what difference it might make.[10]

Figure 18. USGS GAP land-cover map.

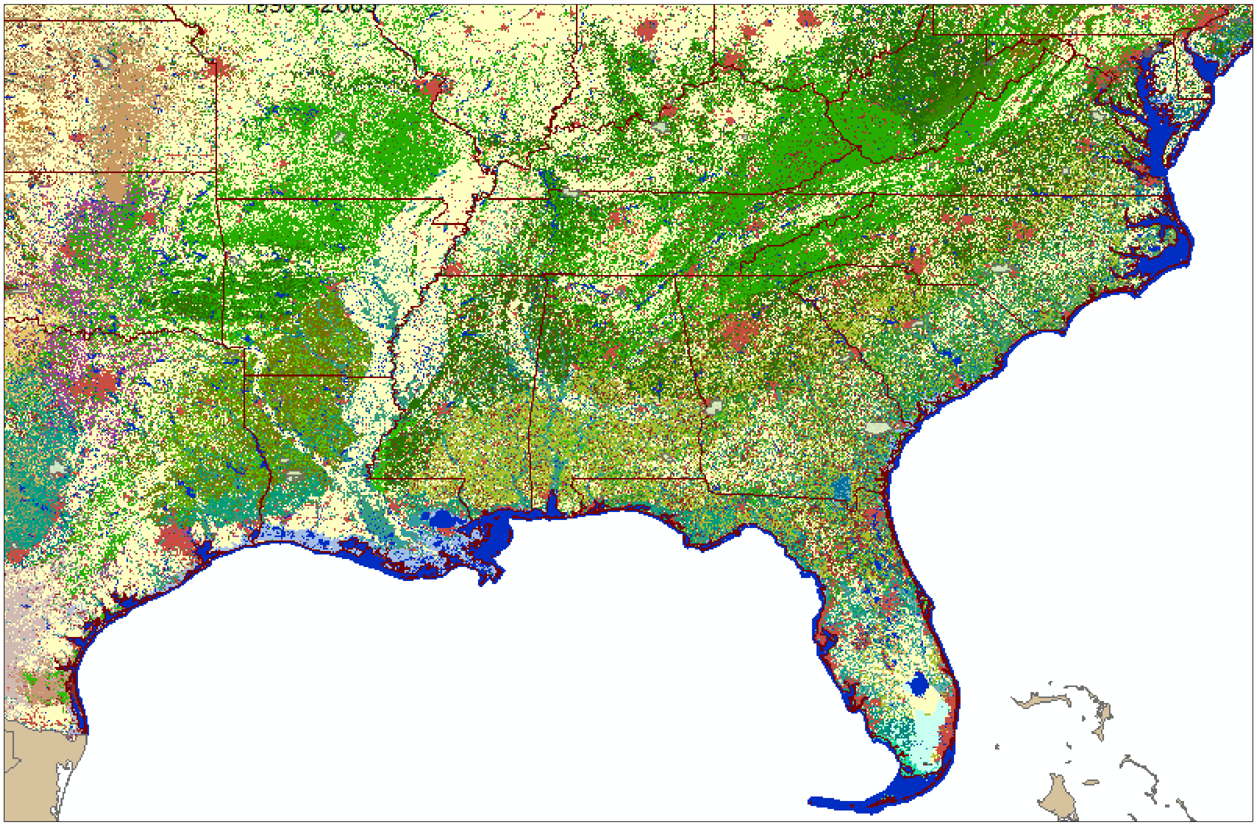
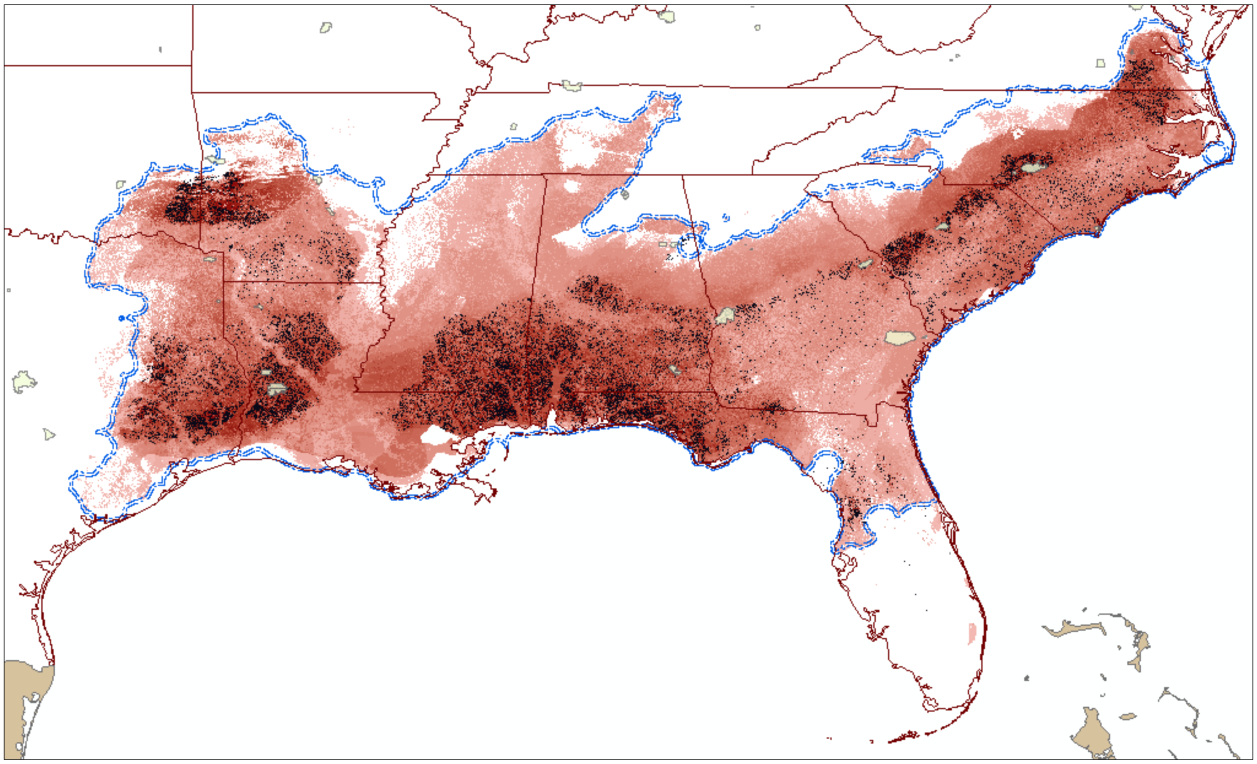


Figure 19 uses the high-contrast color table to show the effect of integrating the GAP land-use data into the Maxent analysis. It reveals that good RCW habitat is restricted along the Mississippi lowland in a manner similar to that which resulted from the integration of the physiographic regions map discussed above. The best locations for RCW potential habitat closely correspond with the GAP potential habitat locations (black dots) used as the sample points in all of these analyses. In Figure 19, the potential habitat ends at the white regions, which correspond to a probability level of 0.1. For comparison to the analysis without land use, the extent of the original analysis (also at the probability level of 0.1) is shown in the figure as the double dashed blue line. Many of the edges are the same. Notable exceptions are similar to those already pointed out in the physiographic analysis discussion.

[10] Analysis was also done with another land cover map using the ESA GlobCover 2009 input at http://due.esrin.esa.int/globcover/. The results were similar.

Figure 19. Maxent analysis with integrated GAP land-use data. The GAP potential habitat locations (black dots) are used as the sample points in all of these analyses.



Land use was the seventh most important factor affecting this analysis, but it contributed 4.2% to the overall model — more than the physiographic data did. Although land cover was not the most important factor, it had a great influence on the result. In the jackknife test, the environmental variable with highest gain when used in isolation was land cover, which therefore appears to have the most useful information by itself. The environmental variable that decreases the gain the most when it is omitted is also land cover, which therefore appears to have the most information that isn't present in the other variables. As one might expect, the land-cover type that provided the best habitat was coastal plain pine woodlands. Those ecosystem/land-use types that are the best habitats within the reddish area of Figure 19 are presented in Table 8 along with their corresponding lambdas. Lambdas provide an indication of the strength of the relationship between independent and dependent variables. Most types listed are pines, often Longleaf and Shortleaf Pine. This listing confirms the common knowledge that the RCW prefers those two pine species. There is the single strange category "Managed Tree Plantation." It is particularly prevalent in eastern Texas. It is not clear why this land cover appears in this table.

Table 8. Ecosystem/land use types that are the best habitats for RCW and their level of fit (Lambda).

Lambda	ECOLSYS_LU
1.43467	Florida Longleaf Pine Sandhill- Open Understory Modifier
1.20204	Ozark-Ouachita Shortleaf Pine-Oak Forest and Woodland
0.95885	Ozark-Ouachita Dry-Mesic Oak Forest
0.79951	West Gulf Coastal Plain Pine-Hardwood Forest
0.66324	West Gulf Coastal Plain Wet Longleaf Pine Savanna and Flatwoods
0.6005	West Gulf Coastal Plain Upland Longleaf Pine Forest and Woodland
0.59063	West Gulf Coastal Plain Sandhill Oak and Shortleaf Pine Forest and Woodland
0.52798	East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland - Open Understory Modifier
0.5083	East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland - Loblolly Modifier
0.49886	Atlantic Coastal Plain Fall-line Sandhills Longleaf Pine Woodland - Open Understory
0.4886	Atlantic Coastal Plain Fall-Line Sandhills Longleaf Pine Woodland - Loblolly Modifier
0.46723	East Gulf Coastal Plain Near-Coast Pine Flatwoods - Open Understory Modifier
0.46598	West Gulf Coastal Plain Southern Calcareous Prairie
0.45395	Atlantic Coastal Plain Fall-line Sandhills Longleaf Pine Woodland - Scrub/Shrub Understory
0.44573	Managed Tree Plantation
0.36079	Southern Coastal Plain Blackwater River Floodplain Forest
0.33033	East Gulf Coastal Plain Southern Mesic Slope Forest
0.31563	West Gulf Coastal Plain Small Stream and River Forest
0.20904	East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland - Offsite Hardwood Modifier
0.17905	Atlantic Coastal Plain Upland Longleaf Pine Woodland
0.10639	Atlantic Coastal Plain Dry and Dry-Mesic Oak Forest
0	South Florida Cypress Dome
-0.0174	Developed, Low Intensity
-0.0515	East Gulf Coastal Plain Small Stream and River Floodplain Forest
-0.0604	Open Water (Fresh)
-0.1473	Disturbed/Successional - Grass/Forb Regeneration
-0.4613	Pasture/Hay
-0.6268	Cultivated Cropland

Adding land cover information to the analysis results in better identification of existing RCW likely habitat but detracts from identifying the potential distribution of habitat.

The three analyses in this section (changing the color table, integrating physiographic regions, and integrating land-cover data) were attempts to correct the original identification of the lower Mississippi lowlands as suitable habitat. It is significant that all three analyses reduced the suitability of the upper Mississippi lowlands while indicating that the lower Mississippi lowlands are still potentially viable habitat. It is possible that, bioclimatically, these areas are indeed optimal for supporting RCW popu-

lations, but the intense human use of this flat landscape for agriculture has eliminated tree species required by the RCW. Consideration of the attractiveness of land for human agriculture may improve future analyses.

3.3 RCW thresholds and climate change

3.3.1 RCW thresholds at Army installations

To answer the question of whether RCW occurrence falls within the defined tolerances at Army installations, the bioclimatic values for two sample installations are determined to see if the RCW may currently be bioclimatically stressed (Table 9).

Table 9. Bioclimatic threshold values for RCW occurrence at two Army locations.

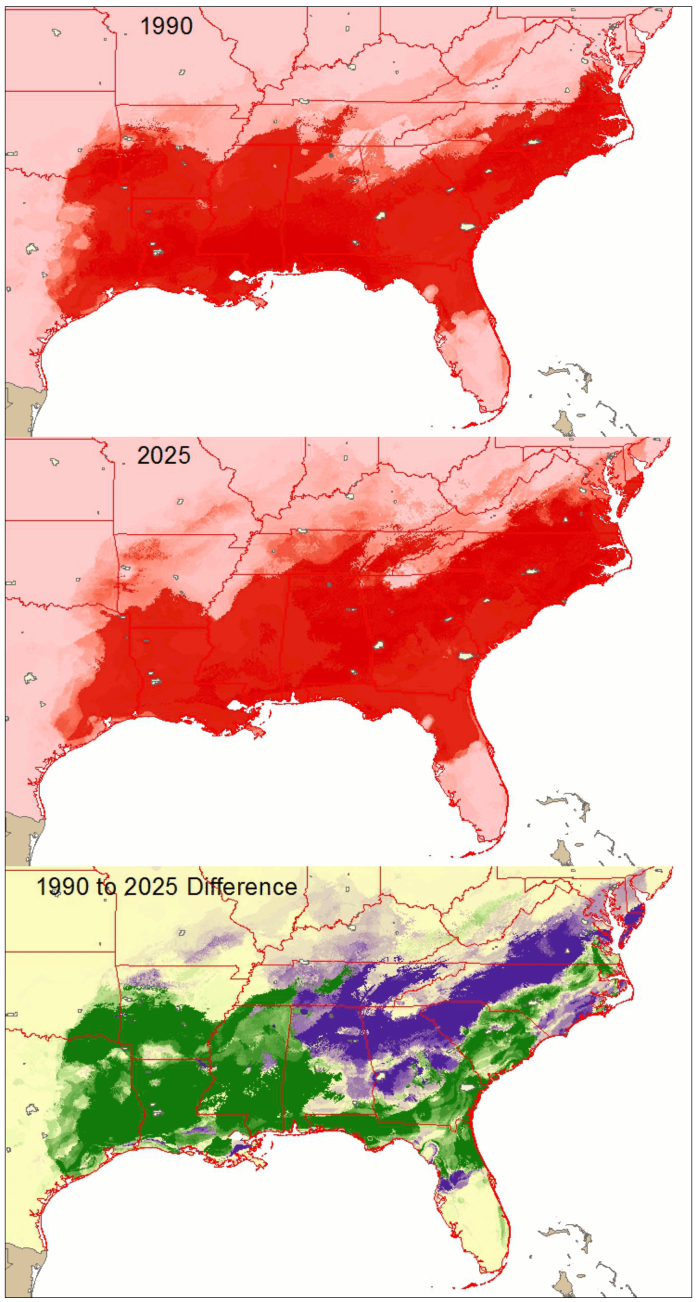
Factor	Bioclimatic Concern	Lower Threshold	Fort Stewart	Fort Benning	Upper Threshold
BIO17	Precipitation of Driest Quarter (cm)	18.0	20.1	23.0	36.0
BIO12	Annual Precipitation (in centimeters)	110.0	122.3	120.9	170.0
BIO10	Mean Temperature of Warmest Quarter (°C)	24.0	26.9	26.4	27.8
BIO1	Annual Mean Temperature (°C)	14.0	19.2	18.0	22.0
BIO6	Min Temperature of Coldest Month (°C)	-4.5	3.5	1.7	8.0
BIO4	Temperature Seasonality (standard deviation*10)	4500.0	6290.0	6844.0	8100.0
BIO11	Mean Temperature of Coldest Quarter (°C)	4.0	10.7	8.9	15.0
BIO14	Precipitation of Driest Month (cm)	5.0	5.8	5.2	11.3
BIO8	Mean Temperature of Wettest Quarter (°C)	7.5	26.9	13.8	27.0
BIO3	Isothermality (mean diurnal range/temperature annual range)	34.0	41.0	42.0	51.0
BIO13	Precipitation of Wettest Month (cm)	11.0	15.9	12.9	22.0
BIO9	Mean Temperature of Driest Quarter (°C)	4.5	15.2	18.5	28.0
BIO20	Maximum number of consecutive dry months (<100 mm/year)	None	5.0	4.0	6.0
BIO2	Mean Diurnal Range (Mean of monthly (max temp -min temp)) (°C)	10.4	12.4	13.2	14.3
BIO19	Precipitation of Coldest Quarter (cm)	21.0	26.9	33.9	47.0
BIO18	Precipitation of Warmest Quarter (cm)	21.0	44.2	31.4	60.0
BIO15	Precipitation Seasonality (Coefficient of Variation)	7.0	30.0	22.0	50.0
BIO7	Temperature Annual Range (P5-P6) (°C)	25.0	30.1	31.4	37.5
BIO5	Max Temperature of Warmest Month (°C)	31.0	33.4	33.0	35.0
BIO16	Precipitation of Wettest Quarter (cm)	31.0	44.2	35.2	60.0

The table reveals that at both Fort Stewart and Fort Benning, the current conditions fall within the RCW thresholds.

3.3.2 RCW and climate change

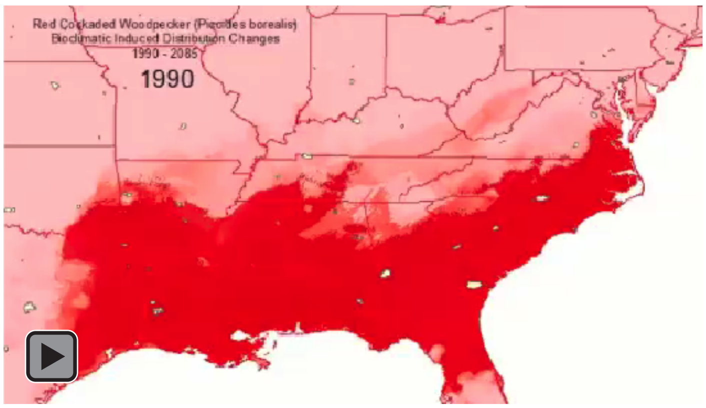
Maxent allows the user to submit additional changed data to the program. In this case, the bioclimatic data for 2025 were submitted to see how different the potential distribution of RCW bioclimatic habitat would be by then (Figure 20).

Figure 20. Initial 1990 RCW distribution (top), 2025 distribution (middle), and difference between the two (bottom). Blue shows increase in desirable distribution, green shows decrease, pale shows no change, and white polygons show installations.



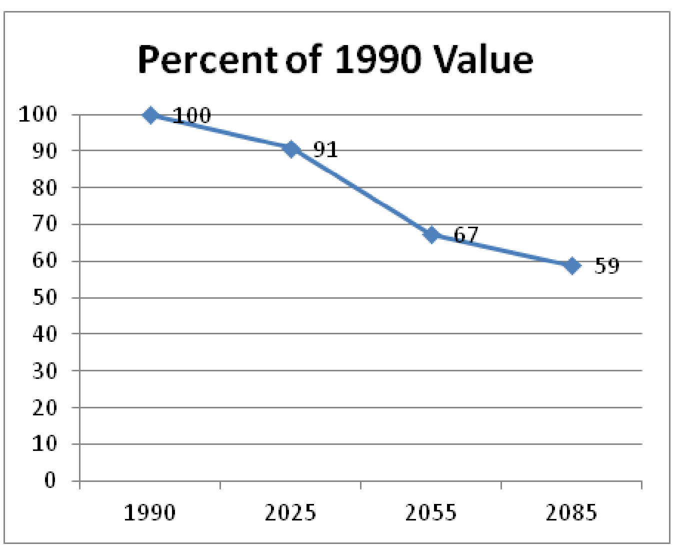
This figure shows the differences between the initial and future distributions. Notice Fort Benning is in the area of improved habitat quality while Fort Stewart is in the area of decreased habitat quality. In the longer time frame (Figure 21 animation) it shows the RCW distribution tends to trend northeast by 2025 but then the acceptable distribution shrinks in the north and southeast by 2085.

Figure 21. Animation of RCW probability distribution 1990–2085 (click to run).



The animation shows that by 2085 the RCW distribution is smaller in extent and less intensely red (i.e., the probability of good habitat has decreased). The RCW distribution decrease is shown by summing the probabilities at each time period to generate the chart in Figure 22. Figure 22 shows that the habitat decreases in the near term (by 2025) by nearly 10% and by 2085 by over 40%. Thus the RCWs potential existence will be challenged by climate-change effects.

Figure 22. RCW habitat over time due to climate change.



3.3.3 Climate change effects on threshold ranges for RCW at Army installations

We now return to a detailed look at the two target Army installations using the modeled thresholds to determine the danger to the RCW at Forts Stewart and Benning. To accomplish this, a somewhat more objective evaluation of the current situation, as compared to that in 2025, was developed. Using the range between the upper and lower thresholds for each of the model input bioclimatic layers, it was assumed that the midpoint of that range is the most beneficial situation for the species. For each component, the current (i.e., 1990) location of the installation within that range as a percentage of distance from the midpoint and the amount of change between that value and the similar value for 2025 was identified. The result is either a positive value (the installation is moving toward the midpoint) or a negative value (which means it is moving away from the midpoint). Finally each change amount was multiplied by the percentage contribution of that component to the RCW model. The result was a weighted value. Larger positive values for 2025 imply a better habitat, smaller values (negatives) a poorer habitat. Table 10 shows the results of the calculations.

This table shows that the first potential problem for either installation comes from about a 20% decrease in habitat suitability due to the increase in the Mean Temperature of Warmest Quarter. Normally a change of this amount is only slightly worrisome. However, at Fort Stewart, that amount puts the Mean Temperature of Warmest Quarter above (lighter red box) the normal range for RCW. Fort Stewart, therefore, is likely to experience much more difficulty in encouraging successful RCW colonies; the installation will be less inviting to the RCW due to changed climate. The next most important inhibiting concern for both installations is the increase in the Annual Mean Temperature. In both cases the weighted concern importance is less than 10%. No other concerns exhibit significant negative values. Isothermality at both installations falls below the normal RCW range.

Table 10. Bioclimatic threshold changes for the RCW at two Army locations due to climate alteration.

Bioclimatic Thresholds For the Occurance of Red Cockaded Woodpecker at Army Locations												
Bio Num	Bioclimatic Concern	% Importance in Model	Lower Threshold	Fort Stewart 1990 value	Fort Benning 1990 value	Range Midpoint	Fort Stewart 2025 value	Fort Benning 2025 value	Fort Stewart 2025 value outside threshold	Import Relative to greatest % Import in Model	Stewart 2025 weighted % dif from midpoint	Benning 2025 weighted % dif from midpoint
BIO17	Precipitation of Driest Quarter (cm)	38.4	18.0	20.1	23.0	27.00	21.9	22.5	0	1.000	28.33	25.00
BIO12	Annual Precipitation (in centimeters)	21	110.0	122.3	120.9	140	127.7	125.4	0	0.547	11.21	13.31
BIO10	Mean Temperature of Warmest Quarter (deg C)	14.5	24.0	26.9	26.4	25.9	28.2	27.8	1	0.378	-22.85	-18.88
BIO1	Annual Mean Temperature (deg C)	12.5	14.0	19.2	18.0	18	20.1	19	0	0.326	-8.54	-4.07
BIO6	Min Temperature of Coldest Month (deg C)	3.2	-4.5	3.5	1.7	1.75	4.1	1.8	0	0.083	-1.57	-0.03
BIO4	Temperature Seasonality (standard deviation*10)	2.2	4500.0	6290.0	6844.0	6300	6550	7128	0	0.057	-0.40	-1.32
BIO11	Mean Temperature of Coldest Quarter (deg C)	1.7	4.0	10.7	8.9	9.5	11.4	9.5	0	0.044	-0.76	0.00
BIO14	Precipitation of Driest Month (cm)	1.6	5.0	5.8	5.2	8.15	5.9	5.5	0	0.042	1.49	1.75
BIO8	Mean Temperature of Wettest Quarter (deg C)	1.4	7.5	26.9	13.8	17.25	28.2	18.1	1	0.036	-2.05	-0.16
BIO3	Isothermality (mean diurnal range/temperature annual range)	0.9	34.0	41.0	42.0	42.5	3.9	4.1	-1	0.023	5.32	5.29
BIO13	Precipitation of Wettest Month (cm)	0.7	11.0	15.9	12.9	16.5	16.7	14.5	0	0.018	-0.03	0.33
BIO9	Mean Temperature of Driest Quarter (deg C)	0.6	4.5	15.2	18.5	16.25	16	19.4	0	0.016	0.02	-0.21
BIO20	Maximum number of consecutive dry months (<100 MM/year)	0.5	0.0	5.0	4.0	3	4	2	0	0.013	-0.22	0.22
BIO2	Mean Diurnal Range (Mean of monthly (max temp -min temp)) (deg C)	0.3	10.4	12.4	13.2	12.35	12.2	13.8	0	0.008	0.03	-0.29
BIO19	Precipitation of Coldest Quarter (cm)	0.2	21.0	26.9	33.9	34	27.1	34.6	0	0.005	0.14	-0.01
BIO18	Precipitation of Warmest Quarter (cm)	0.2	21.0	44.2	31.4	40.5	46.2	35	0	0.005	-0.08	0.07
BIO15	Precipitation Seasonality (Coefficient of Variation)	0.1	7.0	30.0	22.0	28.5	31	23	0	0.003	-0.02	0.03
BIO7	Temperature Annual Range (P5-P6) (deg C)	0.1	25.0	30.1	31.4	31.25	30.4	32.9	0	0.003	0.02	-0.03
BIO5	Max Temperature of Warmest Month (deg C)	0.1	31.0	33.4	33.0	33	34.6	34.8	0	0.003	-0.10	-0.12
BIO16	Precipitation of Wettest Quarter (cm)	0	31.0	44.2	35.2	45.5	46.3	37.7	0	0.000	0.00	0.00

It has been demonstrated how climate changes over time will affect the range of the RCW. The next issues are to determine how the bioclimatic changes will affect the survivability of RCW at Army installations and whether climate change makes the job of RCW preservation for land managers impossible. Using an approach similar to Table 10 above, an analysis of what will happen at all of the Army installations within the RCW range (plus a 50 mile buffer, to be inclusive) was performed. Table 11 presents the results for the two time frames of 1990 and 2025. It represents an abridged version of Table 10, and addresses all the regional installations in

less detail. In Table 11, if a bioclimatic concern for that installation is below a threshold, it is color-coded dark red, those above a threshold are color coded light red. The table shows those concerns that define 91.8% of the Maxent RCW model.

Table 11. Bioclimatic threshold modifications for the RCW because of climate change at all installations within its range.

Bioclimatic Concern	Within RCW Range ?	Precipitation of Driest Quarter (10Xcm)		Annual Precipitation (10Xcm)		Mean Temperature of Warmest Quarter (10Xdeg C)		Annual Mean Temperature (10Xdeg C)		Min Temperature of Coldest Month (10Xdeg C)		Temperature Seasonality (10Xdeg C)	
		Bio17		Bio12		Bio10		Bio1		Bio6		Bio4	
% Importance to RCW Model		38.4		21		14.5		12.5		3.2		2.2	
Installation Name		**1990**	**2025**	**1990**	**2025**	**1990**	**2025**	**1990**	**2025**	**1990**	**2025**	**1990**	**2025**
Anniston Army Depot	Yes	263	269	1380	1436	254	269	160	171	-10	-6	7418	7704
Camp MacKall	Yes	243	254	1188	1266	252	264	159	170	-12	-6	7469	7629
Craney Island Disposal Area	Yes	234	249	1127	1201	249	261	152	163	-3	3	7661	7801
Fort Benning	Yes	211	225	1198	1254	264	278	180	190	16	18	6835	7128
Fort Bragg Military	Yes	235	246	1191	1269	251	263	158	168	-9	-4	7470	7615
Fort Gillem Heliport	Yes	260	265	1283	1346	251	265	160	171	-2	1	7255	7521
Fort Gordon	Yes	231	244	1190	1257	256	270	168	178	0	4	7032	7300
Fort Jackson	Yes	229	243	1189	1264	257	270	168	178	3	8	7140	7344
Fort Lee	Yes	248	256	1116	1192	244	256	143	154	-29	-21	7924	8056
Fort McClellan (Closed)	Yes	270	277	1411	1469	249	264	156	167	-15	-11	7399	7680
Fort McPherson	Yes	263	267	1296	1358	251	265	159	170	-3	0	7329	7589
Fort Monroe	Yes	234	248	1114	1189	250	262	152	163	-2	4	7733	7865
Fort Rucker	Yes	259	271	1382	1419	264	278	185	195	27	29	6486	6785
Fort Story	Yes	237	248	1116	1189	247	259	152	163	0	5	7538	7670
Military Ocean Terminal Sunny Point	Yes	263	277	1405	1475	257	268	172	182	12	16	6774	6923
Fort Eustis	Yes	225	239	1097	1173	245	257	147	158	-16	-8	7812	7959
Fort Polk	Yes	302	298	1446	1443	267	284	186	197	22	27	6703	7059
Fort Stewart	Yes	199	219	1226	1277	269	282	192	201	36	41	6265	6550
Hunter Army Airfield	Yes	189	207	1255	1304	268	281	190	200	39	44	6353	6622
Longhorn Ordnance Army Ammo Plant	Yes	236	230	1225	1211	272	290	182	194	14	17	7221	7619
Louisiana Ordnance Plant	Yes	254	244	1284	1274	269	287	177	189	5	8	7427	7824
Pine Bluff Arsenal	Yes	260	242	1280	1274	266	284	168	180	-2	1	7815	8191
Red River Army Depot	Yes	262	247	1229	1214	266	285	172	184	-5	-1	7646	8062
Camp Joseph T. Robinson	Barely	258	245	1258	1253	265	283	163	175	-17	-12	8147	8520
Fort Chaffee (Closed)	Barely	172	174	972	965	261	280	159	171	-30	-26	8226	8612
U.S. Army Ammunition Depot	No	178	181	1108	1103	266	285	162	174	-26	-23	8326	8740
Fort Pickett (Closed)	No	255	257	1101	1177	237	250	137	148	-40	-32	7888	8047
Blossom Point Field Test Facility	No	231	234	1017	1094	240	252	136	147	-34	-25	8245	8354
Fort A. P. Hill	No	242	248	1071	1148	237	249	134	145	-42	-33	8170	8278
Fort Campbell	No	248	240	1265	1285	248	264	142	154	-41	-34	8479	8704
Milan Arsenal And Wildlife Management Area	No	267	264	1355	1371	249	266	145	158	-37	-31	8319	8583
Redstone Arsenal	No	271	275	1407	1451	252	267	155	167	-18	-13	7710	7984

Table 11 shows that the top 15 Army installations are and will remain within the threshold limits for the RCW. Fort Eustis is interesting in that the annual precipitation is currently too low although by 2025 it will increase so the RCW will be more at home at that location. Several installations (Fort Polk, Fort Stewart, Hunter Army Airfield, Longhorn Ordnance Plant, Louisiana Ordnance Plant, Pine Bluff Arsenal, and Red River Army Depot) that are currently within all of the thresholds presented in Table 11 will move above the threshold for the important concern of Mean Temperature of Warmest Quarter. This is a bioclimatic change threat to the continued existence of the RCW at these locations. Previously, Table 4 showed that the threshold cut is considered “extreme,” so passing the threshold is significant. Longhorn will be over 1 °C above the threshold. These results indicate that land managers will have a difficult time preserving RCW at these installations despite their best efforts because the environment will be less suitable. At these locations, the Army has reason to request that the US Fish and Wildlife Service (FWS) revise the requirements on the Army to carry out a RCW recovery program because the problem the species faces is beyond the ability of the Department of Defense to solve. (Red River Army Depot will have the additional problem that the Temperature Seasonality will drift above that threshold. However, Temperature Seasonality only accounts for 2.2% of the model, so it is not a major concern.) Camp Joseph T. Robinson, Fort Chaffee, U.S. Army Ammunition Depot, Fort Pickett, Blossom Point Field Test Facility, and Fort A.P. Hill are located at the edge of the RCW natural range. Multiple bioclimatic problems crop up at these sites. Attempts to carry out RCW recovery programs at these locations are likely to be futile. The rest of the installations (Fort Campbell, Milan Arsenal and Wildlife Management Area, and Redstone Arsenal) are currently outside the RCW range but have bioclimate values within the threshold needed for the RCW. These are prime locations for the establishment of RCW enhancement programs—particularly at Milan, which is already designated a wildlife management area. Not shown in Table 11, but from an extended version of it, there are threshold limit problems particularly with the Bio8: Mean Temperature of the Wettest Month and Bio15–Precipitation Seasonality concerns. Both problems represent less than 2% of the model importance.

3.3.4 RCW and the individual climate change models

To this point, all evaluations using the average of several GCMs have been presented. The average is used to find scientific-consensus results. However, looking at the issue of thresholds, two issues must be addressed: (1)

whether this species survival is secure under all scenarios and (2) which scenarios make a difference. To address these issues, the original data were used, and the Maxent procedure was run on data from individual scenarios to compare the results with those already presented. The specific models used are:

- GFDL Model – NOAA Princeton (gfdl_cm2_1), ranked as a moderate model
- United Kingdom Hadley Model (ukmo_hadcm3), ranked as a more extreme model
- Canadian (CCCma) Model (cccma_cgcm3_1_t47), ranked as moderate to extreme model

The specific scenarios used are:

- A1(B)—globally homogenous rapid economic growth (with B variation = a balanced usage of both fossil and non-fossil fuel energy sources.)
- A2—locally heterogeneous, regionally oriented economic growth.

The model/scenario combinations represent six alternatives (of the 18 used in the average “consensus evaluations”) that were used in the RCW Maxent runs. Since each combination had 20 bioclimatic concerns, it was necessary to generate 120 maps to support a single combination. The model/scenario combinations were chosen to show those situations that might generate the greatest variation in RCW viability based on climatic concerns. This would be in contrast with the average of all 18 analyses presented to this point.

Table 12 presents the thresholds derived from running the Maxent model on the different individual scenario/model combinations[11].

[11] The average of the 18 different combinations is not the same as the average of the 6 combinations presented here.

Table 12. Bioclimatic thresholds for RCW derived from six GCM/scenario combinations.

Bioclimatic Thresholds For the Occurance of Red Cockaded Woodpecker (Picoides borealis)															
	Scenerio/Model (2025)	Average 18 Scenerios/GMCs		A1B/cccma		A2/cccma		A1B/gfdl		A2/gfdl		A1B/ukmo		A2/ukmo	
Bio Num	Bioclimatic Concern	Lower Threshold	Upper Threshold	Lower Threshold	Upper Threshold	Lower Threshold	Upper Threshold	Lower Threshold	Upper Threshold	Lower Threshold	Upper Threshold	Lower Threshold	Upper Threshold	Lower Threshold	Upper Threshold
BIO17	Precipitation of Driest Quarter (cm)	18.0	36.0	19.0	None	17.0	None	18.5	None	20.0	None	17.0	None	21.0	None
BIO12	Annual Precipitation (in centimeters)	110.0	170.0	109.0	172.0	110.0	170.0	110.0	17.0	110.0	170.0	112.0	160.0	110.0	175.0
BIO10	Mean Temperature of Warmest Quarter (deg	24.0	27.8	25.0	28.0	25.0	28.0	25.5	30.0	25.0	29.5	26.0	31.0	26.0	30.8
BIO1	Annual Mean Temperature (deg C)	14.0	22.0	15.0	22.0	15.0	22.0	15.0	22.8	15.5	22.5	16.5	23.0	16.0	22.7
BIO6	Min Temperature of Coldest Month (deg C)	-4.5	8.0	-3.5	9.5	-4.0	5.5	-3.3	8.0	-4.8	8.0	-2.0	10.0	-3.0	7.5
BIO4	Temperature Seasonality (standard	4500	8100	4900	8800	5000	8800	4900	9000	5000	8900	4500	8200	4700	8500
BIO11	Mean Temperature of Coldest Quarter (deg C)	4.0	15.0	4.5	15.0	4.0	15.5	4.5	15.5	4.0	16.0	6.0	17.0	5.0	17.0
BIO14	Precipitation of Driest Month (cm)	5.0	11.3	4.1	None	4.8	None	5.2	None	5.0	None	4.0	None	4.5	None
BIO8	Mean Temperature of Wettest Quarter (deg C)	7.5	27.0	7.7	28.0	6.5	28.0	6.3	32.0	6.0	28.0	10.5	29.0	10.0	29.0
BIO3	Isothermality (mean diurnal	34.0	51.0	28.0	43.0	18.0	41.0	34.0	49.0	32.5	48.5	35.0	50.0	35.0	57.0
BIO13	Precipitation of Wettest Month (cm)	11.0	22.0	12.0	21.5	12.0	23.0	12.0	24.5	11.0	23.0	12.0	21.5	13.0	22.0
BIO9	Mean Temperature of Driest Quarter (deg C)	4.5	28.0	4.2	None	4.0	None	11.0	None	6.0	None	7.5	None	5.5	None
BIO20	Maximum number of consecutive dry months	None	6.0	None	6.0	None	4.0	None	7.0	None	7.0	None	8.0	None	6.0
BIO2	Mean Diurnal Range (Mean of monthly (max	10.4	14.3	8.0	12.8	4.3	12.5	9.9	14.8	10.0	14.6	12.0	16.0	10.9	17.5
BIO19	Precipitation of Coldest Quarter (cm)	21.0	47.0	20.0	48.0	21.0	47.0	22.0	46.0	21.0	47.0	20.0	47.5	22.0	50.0
BIO18	Precipitation of Warmest Quarter (cm)	21.0	60.0	22.0	60.0	22.0	61.0	22.0	63.0	22.5	61.0	20.0	59.0	21.0	62.0
BIO15	Precipitation Seasonality (Coefficient	7.0	50.0	11.0	42.0	18.0	48.0	16.0	50.0	18.0	40.0	15.0	46.0	10.0	36.0
BIO7	Temperature Annual Range (P5-P6) (deg C)	25.0	37.5	22.5	37.0	23.5	37.5	26.0	40.0	26.0	40.0	24.0	39.0	27.0	42.0
BIO5	Max Temperature of Warmest Month (deg C)	31.0	35.0	29.5	34.0	27.0	34.5	32.0	37.5	32.0	37.5	33.5	39.0	33.0	39.5
BIO16	Precipitation of Wettest Quarter (cm)	31.0	60.0	34.0	61.0	31.0	62.0	31.0	64.0	31.0	63.0	31.0	60.0	31.0	63.0

With these data in hand, it is possible to revisit Table 11. Instead of detailing the effect of the average climate change on RCW thresholds, Table 13 shows the frequency at which individual models predict a climate change beyond the tolerance of the species.

Table 13. The frequency in which individual GCM/scenarios exceeded RCW bioclimatic thresholds.

Bioclimatic Concern	Within RCW Range?	Precipitation of Driest Quarter (10Xcm)	Annual Precipitation (10Xcm)	Mean Temperature of Warmest Quarter (10Xdeg C)	Annual Mean Temperature (10Xdeg C)	Min Temperature of Coldest Month (10Xdeg C)	Temperature Seasonality (10Xdeg C)
		Bio17	Bio12	Bio10	Bio1	Bio6	Bio4
% Importance to RCW Model		38.4	21	14.5	12.5	3.2	2.2
Installation Name							
Anniston Army Depot	Yes	0	0	0	0	0	0
Camp MacKall	Yes	0	0	0	0	0	0
Craney Island Disposal Area	Yes	0	0	0	1	0	0
Fort Benning	Yes	0	0	0	0	0	0
Fort Bragg Military	Yes	0	0	0	0	0	0
Fort Gillem Heliport	Yes	0	0	0	0	0	0
Fort Gordon	Yes	0	0	0	0	0	0
Fort Jackson	Yes	0	0	0	0	0	0
Fort Lee	Yes	0	0	2	3	1	0
Fort McClellan (Closed)	Yes	0	0	0	0	0	0
Fort McPherson	Yes	0	0	0	0	0	0
Fort Monroe	Yes	0	0	0	1	0	0
Fort Rucker	Yes	0	0	0	0	0	0
Fort Story	Yes	0	0	2	1	0	0
Military Ocean Terminal Sunny Point	Yes	0	0	0	0	0	0
Fort Eustis	Yes	0	0	2	2	0	0
Fort Polk	Yes	0	0	2	0	0	0
Fort Stewart	Yes	0	0	2	0	0	0
Hunter Army Airfield	Yes	1	0	2	0	0	0
Longhorn Ordnance Army Ammo Plant	Yes	0	0	2	0	0	0
Louisiana Ordnance Plant	Yes	0	0	2	0	0	0
Pine Bluff Arsenal	Yes	0	0	2	0	0	0
Red River Army Depot	Yes	0	0	2	0	0	0
Camp Joseph T. Robinson	Barely	0	0	2	0	0	2
Fort Chaffee (Closed)	Barely	4	6	2	0	1	2
U.S. Army Ammunition Depot	No	4	1	2	0	1	2
Fort Pickett (Closed)	No	0	0	6	6	2	0
Blossom Point Field Test Facility	No	0	5	3	6	1	1
Fort A. P. Hill	No	0	0	6	6	3	1
Fort Campbell	No	0	0	0	3	3	2
Milan Arsenal And Wildlife Management Area	No	0	0	0	2	2	2
Redstone Arsenal	No	0	0	0	0	0	0

Table 13 presents the same six most important bioclimatic concerns shown in Table 11, but Table 13 only shows the changes that occur by 2025. Fur-

ther, the interpretation of Table 13 is different than that of Table 11. Table 11 showed dark red and light red for each location/bioclimatic-concern that went below or above (respectively) the average of the GCM/scenarios. In Table 13, the darkness of the red indicates how frequently an individual GCM/scenario indicated an installation would be out of the tolerance ranges (but not indicating if it was above or below that range). Twelve possibilities were checked, but only a maximum value of six was possible (because a value cannot be both above and below the range).

Table 13 shows problems seen at Fort Lee, Fort Story and Fort Eustis were averaged away in Table 11. Bio 10 Mean: Temperature of Warmest Quarter remains the biggest issue at Fort Polk, Fort Stewart, Hunter Army Airfield, Longhorn Ordnance Plant, Louisiana Ordnance Plant, Pine Bluff Arsenal, and Red River Depot. As previously mentioned, Army installations farther outside the Maxent-defined range will more frequently have problems in being out of those thresholds.

The analysis shows that installations nearer the edge of the Maxent probability distribution will tend to experience more difficulty preserving an RCW population. It also shows that consensus approach does represent the issues well but, as can be expected, problems suggested by individual GCM/scenario combinations can be overlooked because of the averaging procedure.

4 Modeling Musk Turtle Distribution with Maxent

4.1 Generating the musk turtle probability distribution

4.1.1 Musk turtle data

The Maxent approach was applied to the analysis on another species, *Sternotherus odoratus* (common musk turtle, Figure 23). The musk turtle was chosen because it is a common, non-threatened species that lives on several eastern U.S. installations. It is also a species that is currently under study by other researchers (at Savannah River Laboratory) under the same umbrella project.

Figure 23. *Sternotherus odoratus* (common musk turtle).

The Maxent sample point location data was provided by Savannah River Laboratory (SRL). As described in the source paper (Buhlmann 2009):

> Point locality data for all freshwater turtles and tortoises, but not marine turtles, were obtained from museum-verified records, published accounts, and databases (Iverson 1992b; Iverson et al. 2003; Kiester and Bock 2007); from the literature published since 1992; and from unpublished records provided by the authors.

4.1.2 Initial Maxent musk turtle outputs

The SRL sample locations and the same 20 bioclimatic layers were used to run Maxent for the musk turtles. The probability output map is shown in Figure 24.

Figure 24. Maxent probability output map for the musk turtle (SRL sample locations displayed as dots and the traditional range as a dotted line).

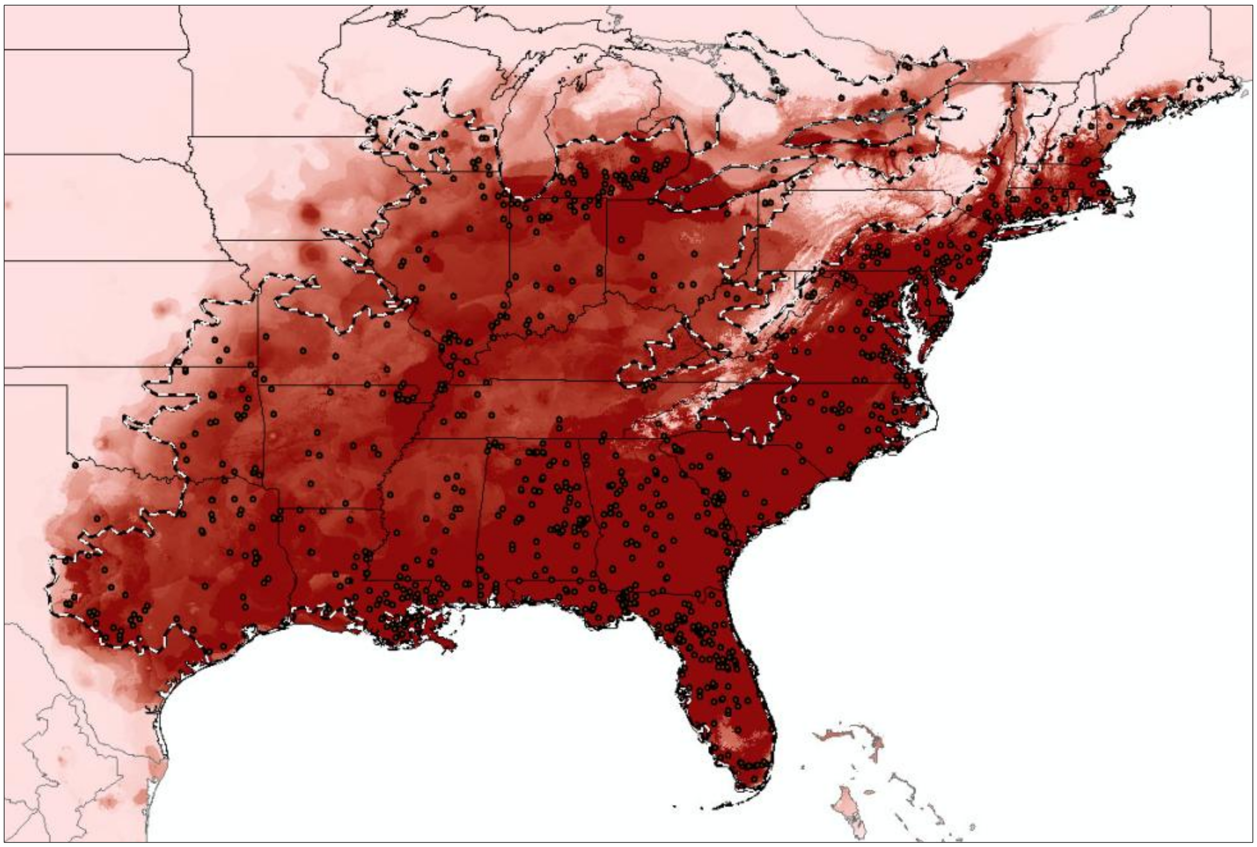


Table 14 shows the contribution of each bioclimatic input to the model. Bio10–Mean Temperature of Warmest Quarter, Bio14–Precipitation of Driest Month, and Bio17–Precipitation of Driest Quarter are the top three contributors, and explain 85.7% of the model inputs. So warmth and dryness matter to the musk turtle.

Table 14. Input variable importance and permutation for the musk turtle model.

Variable	Percent contribution	Permutation importance
bio10	35.8	30.8
bio14	32.7	31.6
bio17	17.2	7.5

Variable	Percent contribution	Permutation importance
bio3	3.2	4.1
bio6	3	1.2
bio4	2	1.5
bio12	1.2	3.4
bio5	0.8	5.3
bio8	0.8	2
bio20	0.8	2.1
bio15	0.6	1.1
bio1	0.4	2.6
bio9	0.4	0.3
bio7	0.3	1.4
bio18	0.3	0
bio2	0.2	3.5
bio13	0.1	0.3
bio19	0.1	0.1
bio16	0	0.1
bio11	0	1.2

4.1.3 Integrating additional layers into the Maxent analysis

Since the habitat for the musk turtle is largely confined to the lowlands[12], additional non-dynamic data layers were integrated into the analysis. The caveat to keep in mind is that the source location data for the turtle may not be accurate enough to correlate with the non-dynamic data. (For example, the source data may be a county-size sighting record while the non-dynamic location data may be accurate within minutes or seconds of latitude/longitude). Nevertheless, the musk turtle prefers creeks, pools, brooks, and medium river areas that are permanent with a slow current (Figure 25)

[12] NatureServe. 2013. NatureServe Explorer: An online encyclopedia of life [web application]. Version 7.1. NatureServe, Arlington, Virginia. Available http://www.natureserve.org/explorer. (Accessed: July 29, 2013).

Figure 25. Prime musk turtle habitat along Upatoi Creek on Fort Benning.

For the purposes of modeling the turtle range, this suggests that potentially useful non-dynamic input maps might be:

- a landform map showing uplands, lowlands, etc. (categorical data)
- a watershed accumulation map which might be able to indicate locations of middle-sized streams (continuous data)
- small streams as accumulation locations of value 3 or greater
- stream orders (categorical data)
- a separate map showing uplands only (i.e., a category to weigh heavily against).

As a potential input, “avoidance of urban areas” was rejected because the turtle source points are partly based on historical sightings, in which case the current urban extent is possibly misleading.

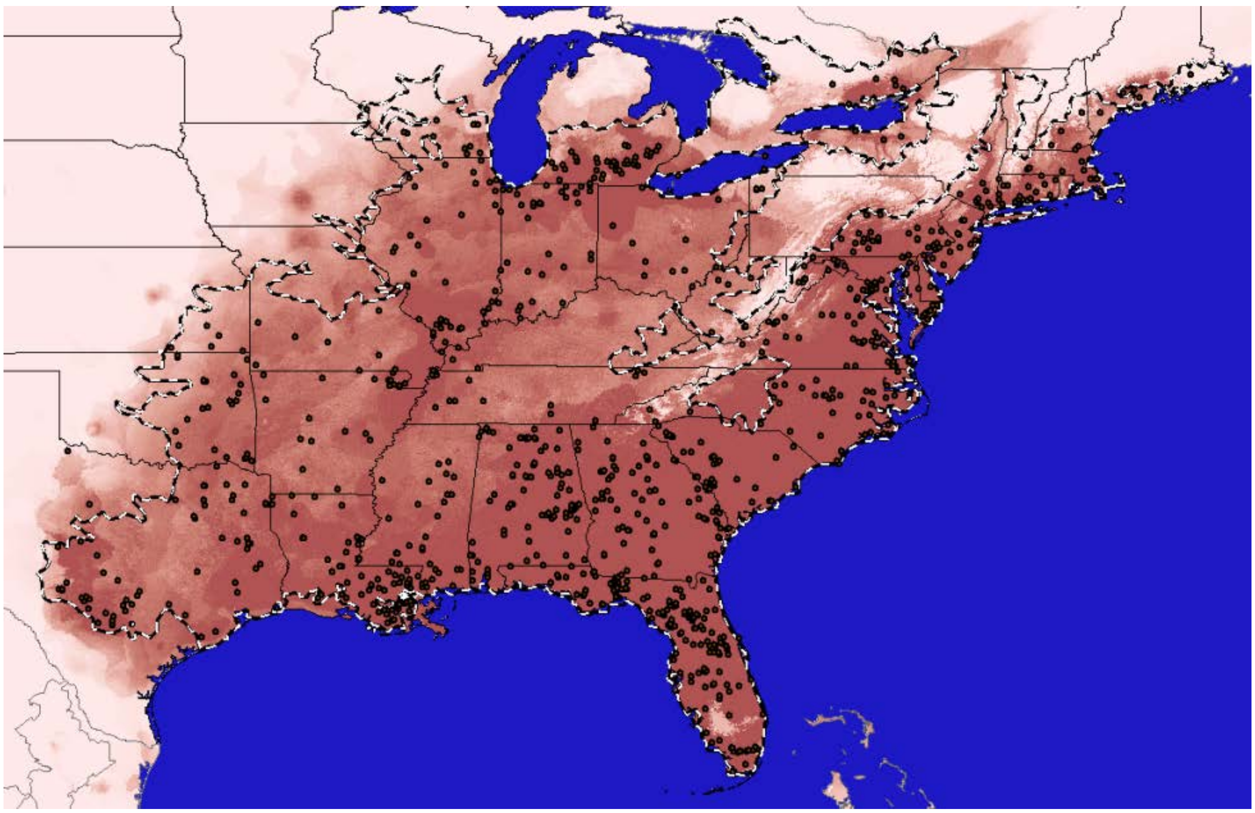
An analysis of various combinations of the non-dynamic inputs was run. It found:

- Every time a landform concern is added, the turtle is more constrained to riverine areas.
- If small streams (accumulations of at least three or greater) are included, modeling is fully constrained to riverine areas because the input maps contain values that remove those locations from any further

analysis. Therefore, using the accumulation map instead is more appropriate.

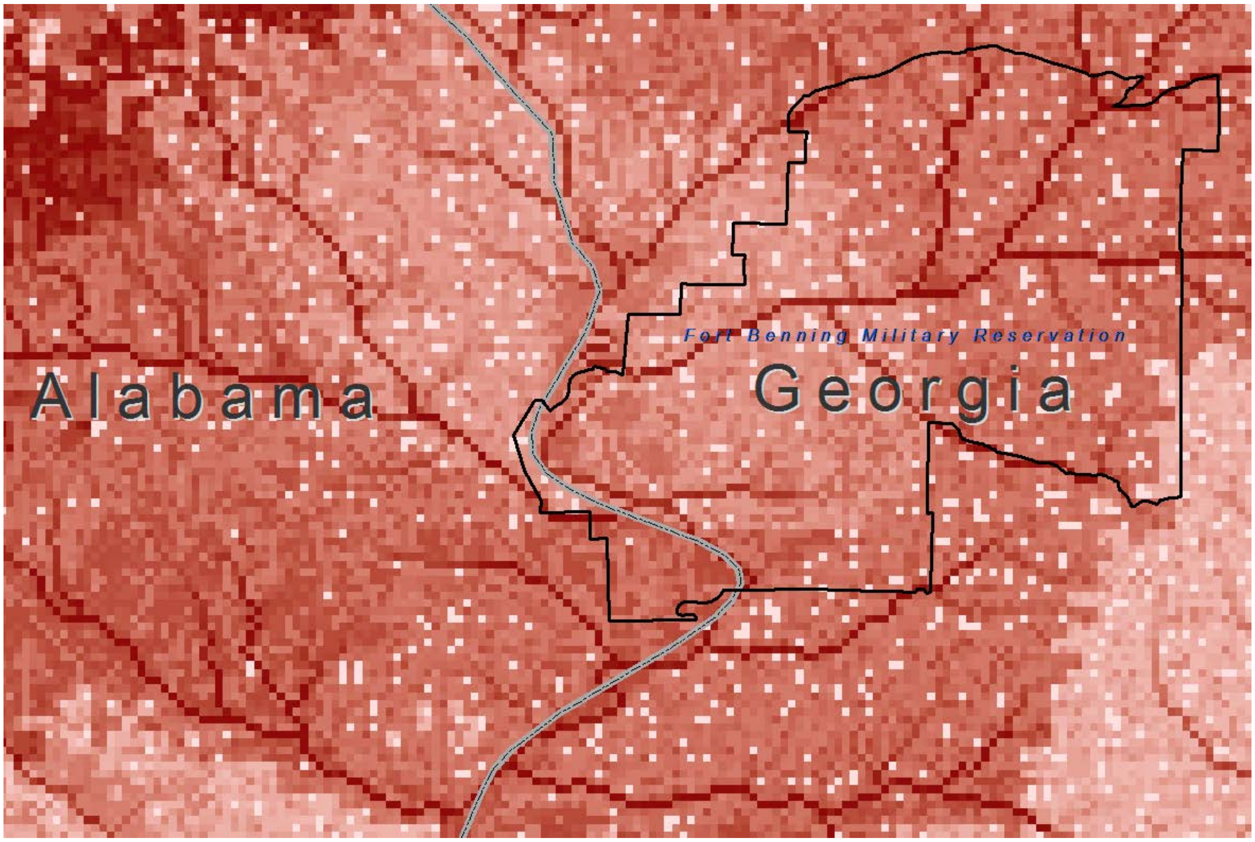
- Adding only the accumulation model and the landform morphology derived from the topographic data produced the most appropriate results. The resulting probability distribution for the musk turtle is shown in Figure 26.

Figure 26. The Maxent musk turtle distribution determined by adding to the bioclimatic data the accumulation model and the landform morphology derived from the topographic data.



Looking at those locations near Fort Benning, most of the area appears to be the same. Even though the color table used for the national distribution makes the entire Fort Benning area look like all the same good habitat, the probability values in this small region range from 0.735459 to 0.308126. Figure 27 shows what the region surrounding Fort Benning looks like if the color table is stretched to reflect this local variation.

Figure 27. Detailed view of musk turtle habitat around Fort Benning using the two topographic inputs in the model.



The local difference is obvious: Fort Benning, particularly along the Upatoi Creek (see Figure 25), is good musk turtle habitat while just to the southeast, the abundance of quality habitat is decreased. The model has tended to favor lowlands, which conforms with the habitat descriptions for the musk turtle.

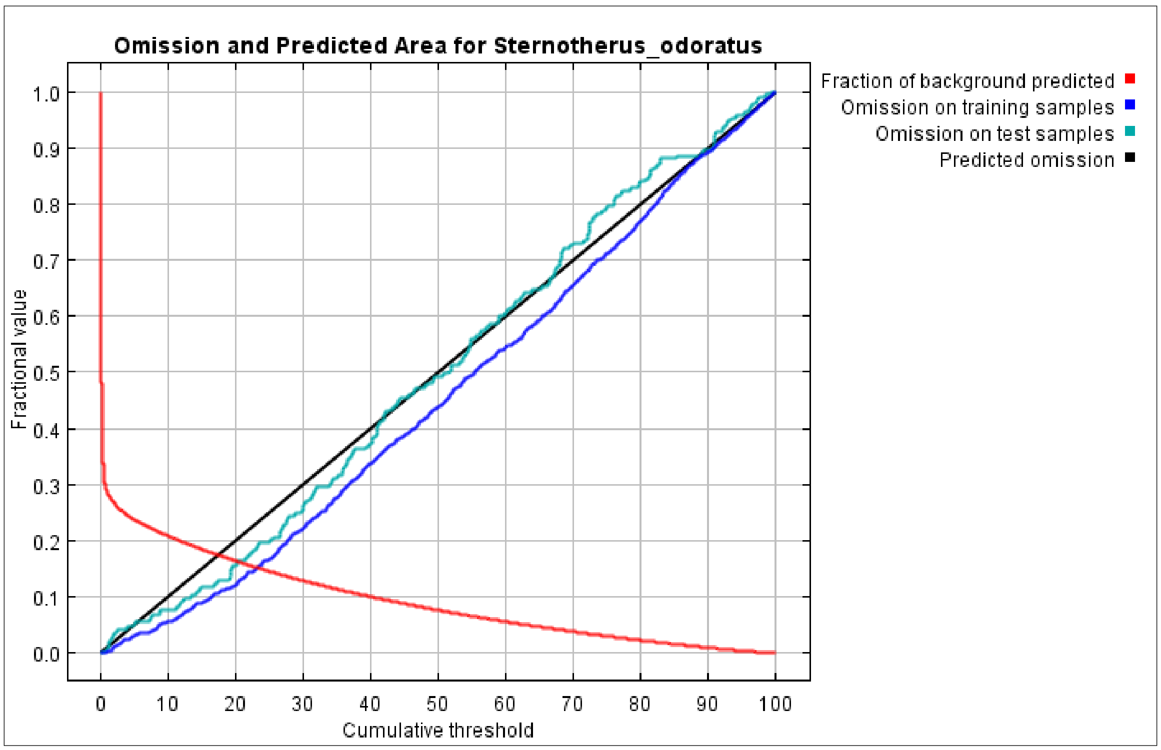
4.2 Evaluation of the musk turtle model

4.2.1 Musk turtle model chart evaluation

As for the RCW, a review of the statistical evaluation of the Maxent model was done. Test procedures were similar to the RCW runs, so most details need not be repeated here. Figure 28 shows the omission rate and predicted area as a function of the cumulative threshold. Eighty percent of the SRL sites were used to train the model, and 20% (called "testing" data) were set aside so that Maxent could check whether the set-aside data actually fit correctly with the model output. The lack of correctness, or the omission rate (the fraction of the test localities that fall into pixels not predicted as suitable), is calculated both on the training records (blue) and

the test records (pink). In this model, the lines are similar, meaning the model is good. Since the training line (blue) is only slightly below the omission line (black) and the test line (pink) follows it closely, the model is good under this test. The fraction of background pixels predicted to be musk turtle habitat that actually is not (area below the red line) drops immediately to a low value and stays low, showing that the model and background areas are not confused.

Figure 28. Graph of the omission rate and predicted area as a function of the cumulative threshold.



In Figure 29, the receiver operating curve (ROC) for both training and test data are shown. Since the black line shown in the ROC represents a useless test that has no discriminatory power, and the size of the area between the black line and the red lines (which reflects the ability of a test to discriminate between presence and non-presence of musk turtles across the range of potential cutoffs) is also large, the test indicates a good model. In fact the area under the curve (AUC) for the musk turtle has the very high value of 0.919.

Figure 29. ROC for both training and test data.

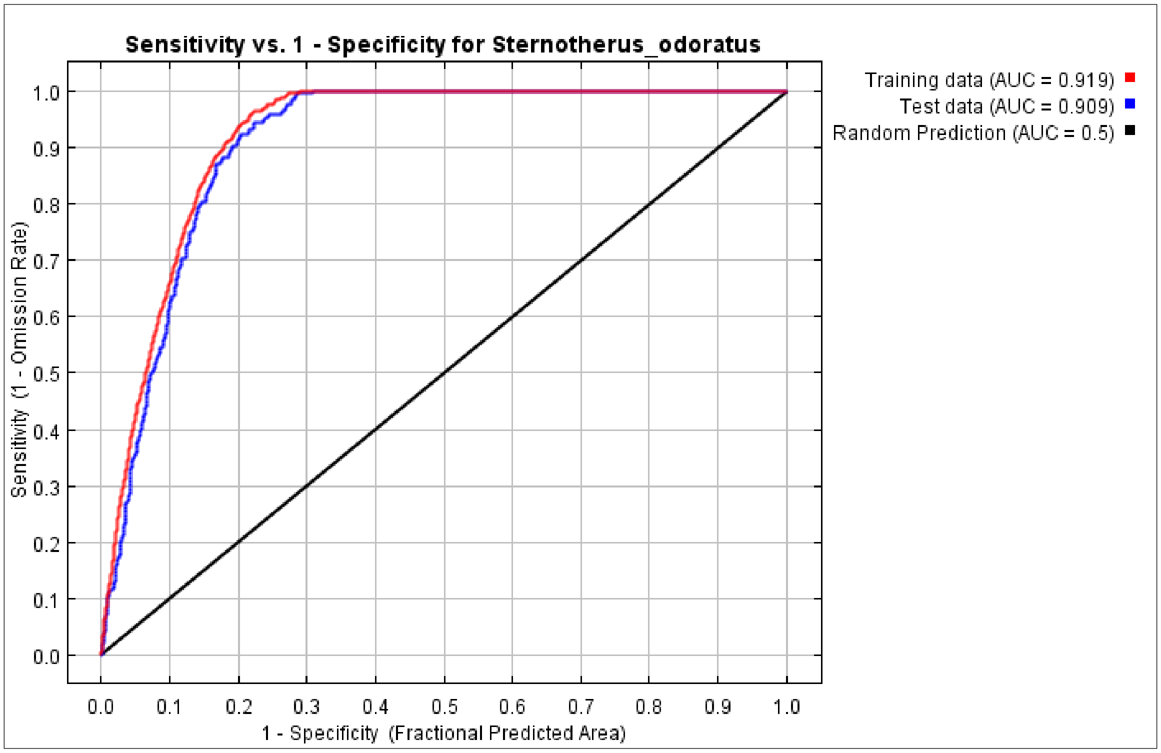


Table 15 shows some metrics for the same musk turtle model as above under a series of differing threshold levels. All p-values are vanishingly small, so the hypothesis "The musk turtle model is close to random" is false under all tests. These evaluations suggest the turtle model is acceptable.

Table 15. A series of different Maxent tests for the viability of the musk turtle model.

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
1.000	0.083	Fixed cumulative value 1	0.285	0.004	0.005	0E0
5.000	0.258	Fixed cumulative value 5	0.238	0.031	0.052	0E0
10.000	0.327	Fixed cumulative value 10	0.209	0.055	0.078	0E0
0.570	0.031	Minimum training presence	0.304	0.000	0.005	0E0
16.354	0.366	10 percentile training presence	0.179	0.099	0.119	0E0
23.270	0.404	Equal training sensitivity and specificity	0.152	0.152	0.192	0E0
7.780	0.307	Maximum training sensitivity plus specificity	0.221	0.039	0.067	0E0
20.326	0.388	Equal test sensitivity and specificity	0.163	0.126	0.161	0E0
11.291	0.335	Maximum test sensitivity plus specificity	0.202	0.062	0.078	0E0

Cumulative threshold	Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
0.570	0.031	Balance training omission, predicted area and threshold value	0.304	0.000	0.005	0E0
3.960	0.224	Equate entropy of thresholded and original distributions	0.246	0.025	0.041	0E0

4.2.2 Thresholds

The correlated marginal response curves in Figure 30 show how each environmental variable affects the Maxent threshold predictions for the musk turtle. The curves illustrate the logistic prediction changes as each environmental variable is changed based on the dependence of predicted suitability both on the selected variable and on dependencies induced by correlations between the selected variable and associated variables. The value shown on the y-axis is predicted probability of suitable conditions, as given by the logistic output format.

The cutoffs for the musk turtle are generally less severe than for the RCW, implying that the turtle is, overall, a more vigorous species. Interestingly, topographic morphology is hardly restricting while there is a significant preference in the accumulation data for the lowest (i.e., smallest stream) locations.

Figure 30. Musk turtle correlated marginal response curves. A value near 1 means the condition is beneficial; a value near 0.5 means the condition is neither limiting or advantageous; a value near zero means the condition is intolerable.

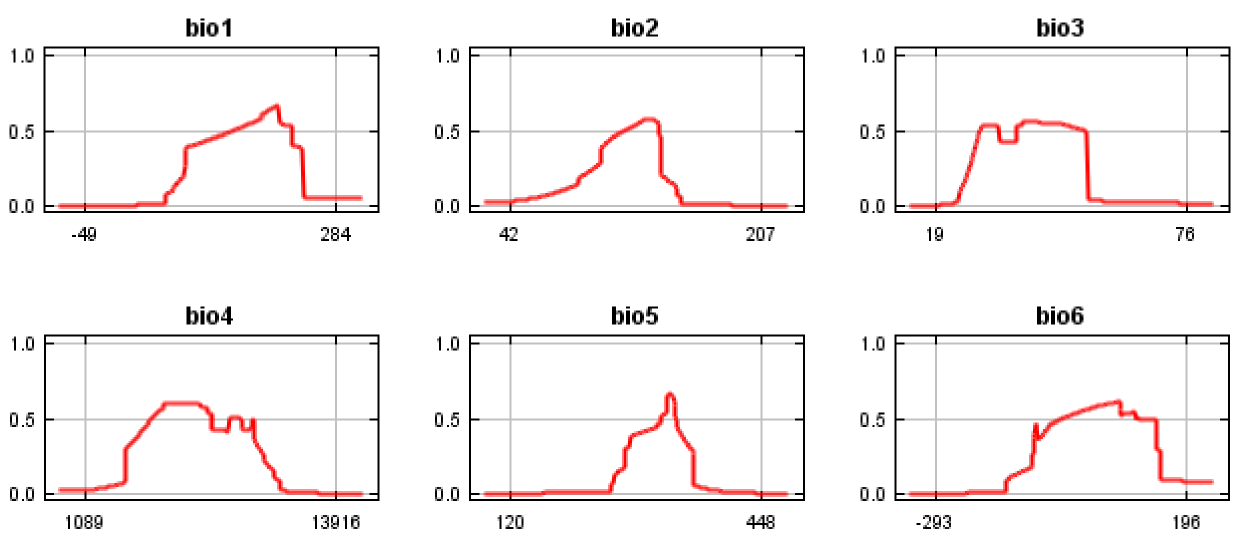
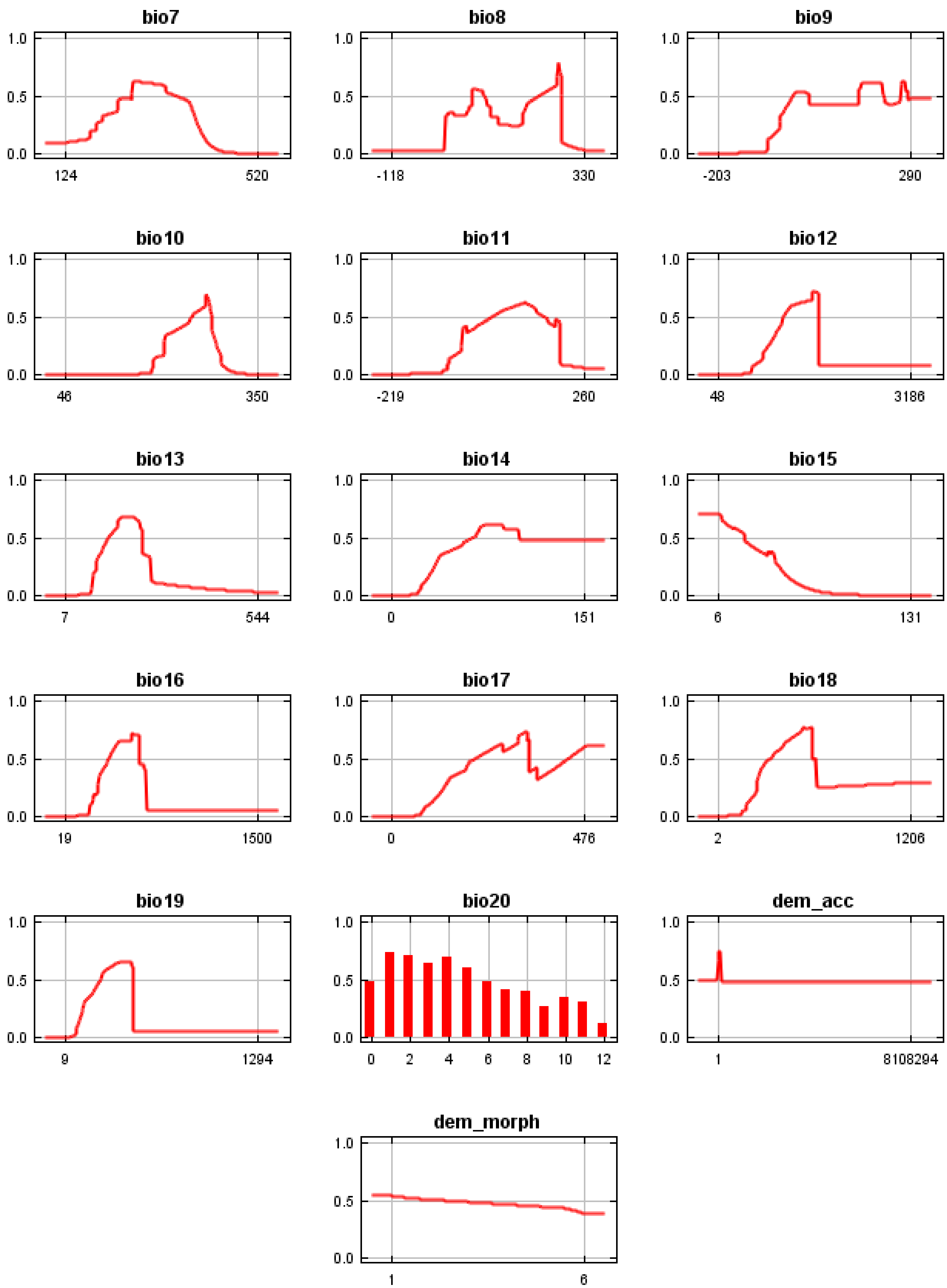


Figure 30 (concluded).



4.2.3 Analysis of variable contributions

Of these 22 variables, which ones matter most in defining the extent of the musk turtle? While the musk turtle model is being trained, Maxent keeps track of which environmental variables are making the greatest contribution to the model. The results are shown in Table 16. Higher permutation values show higher potential for changes in the Percent Contribution column. In this case, some potential variation is seen, but those in the top ranks (the top three or four) will remain the most important in any case.

Table 16. Input variable importance and permutation for the musk turtle model adding the two topography derived data sets.

Variable	Percent contribution	Permutation importance
bio10	37.9	34.1
bio14	32.1	24.5
bio17	17.2	6.2
bio3	2.9	4.1
bio19	1.2	1.5
bio8	1.1	2.6
bio9	1	1.4
bio20	0.9	2.7
bio5	0.8	1.6
bio12	0.8	3.2
bio7	0.7	6
bio11	0.5	0.5
bio18	0.5	0.1
bio13	0.4	0.2
dem_acc	0.4	0.5
bio2	0.4	4.1
bio15	0.3	0.5
bio4	0.2	0.2
bio6	0.2	2.6
dem_morph	0.2	0.4
bio1	0.2	3
bio16	0.1	0.2

It is interesting that the two topographically derived layers are so low on the ranking of percent contribution. It is clear from Figure 27 above that streams were given a high preference, yet this table suggests that the bioclimatic concerns drastically outweighed the influence of topography. Evidently the topography concerns are locally important but not globally so

important in defining the habitat extent. It also suggests that components that contribute less to the distribution map are still very important. Now it is possible to combine the information from the response curves (Figure 30) and Table 16 to generate a table of how important each bioclimatic layer is to the RCW and what its threshold is (Table 17).

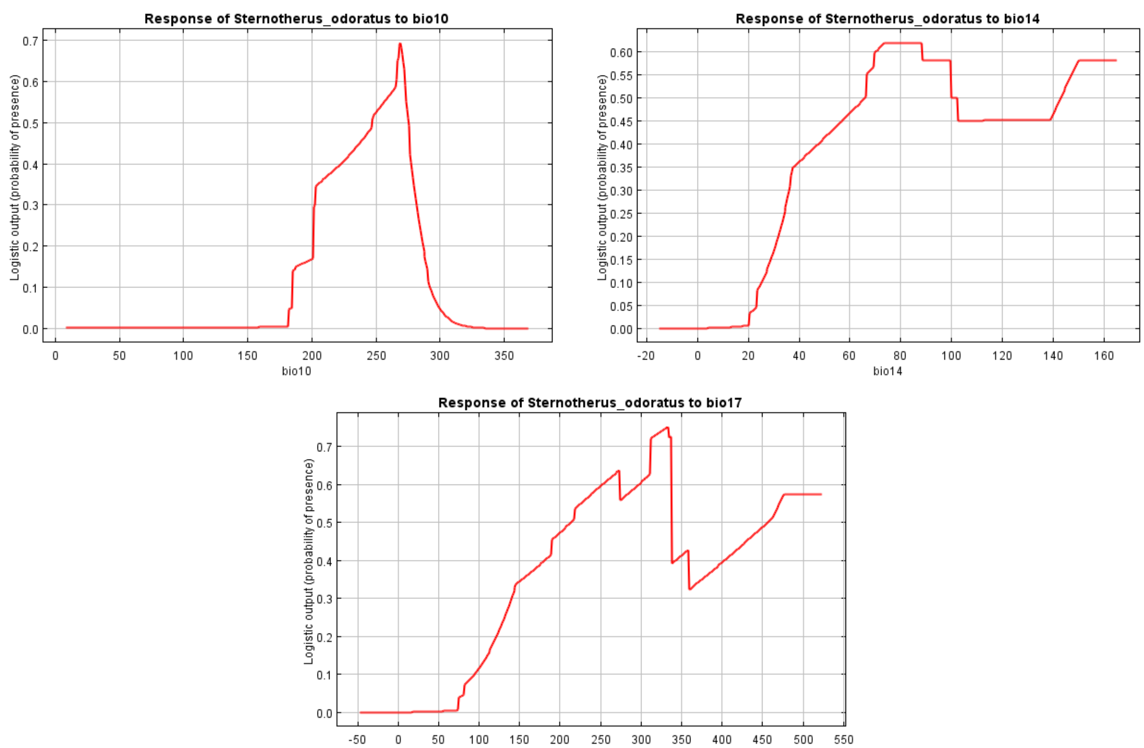
Table 17. Bioclimatic thresholds for the occurrence of the musk turtle.

Bio Num	Bioclimatic Concern	Lower Threshold	Severity	Occurs below Threshold	Upper Threshold	Severity	Occurs above Threshold?	% Importance in Model
BIO10	Mean Temperature of Warmest Quarter (deg C)	18.0	Moderate	No	30.0	Very High	No	37.9
BIO14	Precipitation of Driest Month (cm)	2.0	Moderate Low	No	10.0	Extreme	Yes	32.1
BIO17	Precipitation of Driest Quarter (cm)	7.5	Low	No	None	-	Yes	17.2
BIO3	diurnal range/temperature annual range)	25.0	Very High	No	54.0	Extreme	No	2.9
BIO19	Precipitation of Coldest Quarter (cm)	10.0	High	No	45.0	Extreme	Barely	1.2
BIO8	Mean Temperature of Wettest Quarter (deg C)	0.5	Extreme	No	27.0	Extreme	Barely	1.1
BIO9	Mean Temperature of Driest Quarter (deg C)	-8.0	Very High	No	28.0	None	Yes	1
BIO20	Maximum number of consecutive dry months (<100 MM/year)	None	-	-	11.0	Low	Yes	0.9
BIO5	Max Temperature of Warmest Month (deg C)	25.0	High	No	36.0	Very High	No	0.8
BIO12	Annual Precipitation (in centimeters)	55.0	Moderate Low	No	170.0	Extreme	Barely	0.8
BIO7	Temperature Annual Range (P5-P6) (deg C)	18.0	Moderate Low	Yes	40.0	Moderate Low	Some	0.7
BIO11	Mean Temperature of Coldest Quarter (deg C)	-9.0	Moderate Low	No	20.0	Extreme	Barely	0.5
BIO18	Precipitation of Warmest Quarter (cm)	18.0	Moderate	No	60.0	Extreme	Yes	0.5
BIO13	Precipitation of Wettest Month (cm)	8.5	High	No	25.0	High	Some	0.4
dem_acc	Model from Digital Elevation Model	0.0	Extreme	Barely	1.0	Extreme	No	0.4
BIO2	Mean Diurnal Range (Mean of monthly (max temp -min temp)) (deg C)	8.0	Moderate High	Some	15.5	Very High	No	0.4
BIO15	Precipitation Seasonality (Coefficient of Variation)	None	-	Yes	80.0	Low	No	0.3
BIO4	Temperature Seasonality (standard deviation*10)	3400.0	Very High	No	10000.0	Very High	No	0.2
BIO6	Min Temperature of Coldest Month (deg C)	-15.5	High	No	15.0	Very High	No	0.2
dem_morph	Landform Morphology from Digital Elevation Model	None	-	Yes	5.5	High	Barely	0.2
BIO1	Annual Mean Temperature (deg C)	6.0	Very High	No	24.0	Very High	Barely	0.2
BIO16	Precipitation of Wettest Quarter (cm)	20.0	Very High	No	63.0	Extreme	Barely	0.1

For the musk turtle, the controlling bioclimatic factors (70% contribution to the musk turtle model) are the mean temperature of warmest quarter and precipitation of driest month. The detailed marginal response curves

for the three most important bioclimatic concerns are shown in Figure 31. Bio10–Mean Temperature of Warmest Quarter has both and upper and lower threshold; the lower threshold is 18 °C and the probability increases moderately from that point. The upper limit of 30 °C is a semi-sharp limit above which the musk turtle will not survive. Mean temperature of warmest quarter is limiting. However, both Bio14–Precipitation of Driest Month and Bio17–Precipitation of Driest Quarter have only lower thresholds (which make sense for an amphibian), but neither is severe. They are similar to each other in concept. For the precipitation of driest month, the lower threshold is 2 cm, a cutoff limit below which the musk turtle does not occur; while the upper limit of 10 cm is also a sharp limit above which musk turtle will not survive. Mean temperature of warmest quarter therefore is more important in limiting the musk turtle potential occurrence. Precipitation of Driest Quarter is the next most important concern (17.2% contribution to the musk turtle model).

Figure 31. The detailed marginal response curves for the musk turtle for the three most important bioclimatic concerns.

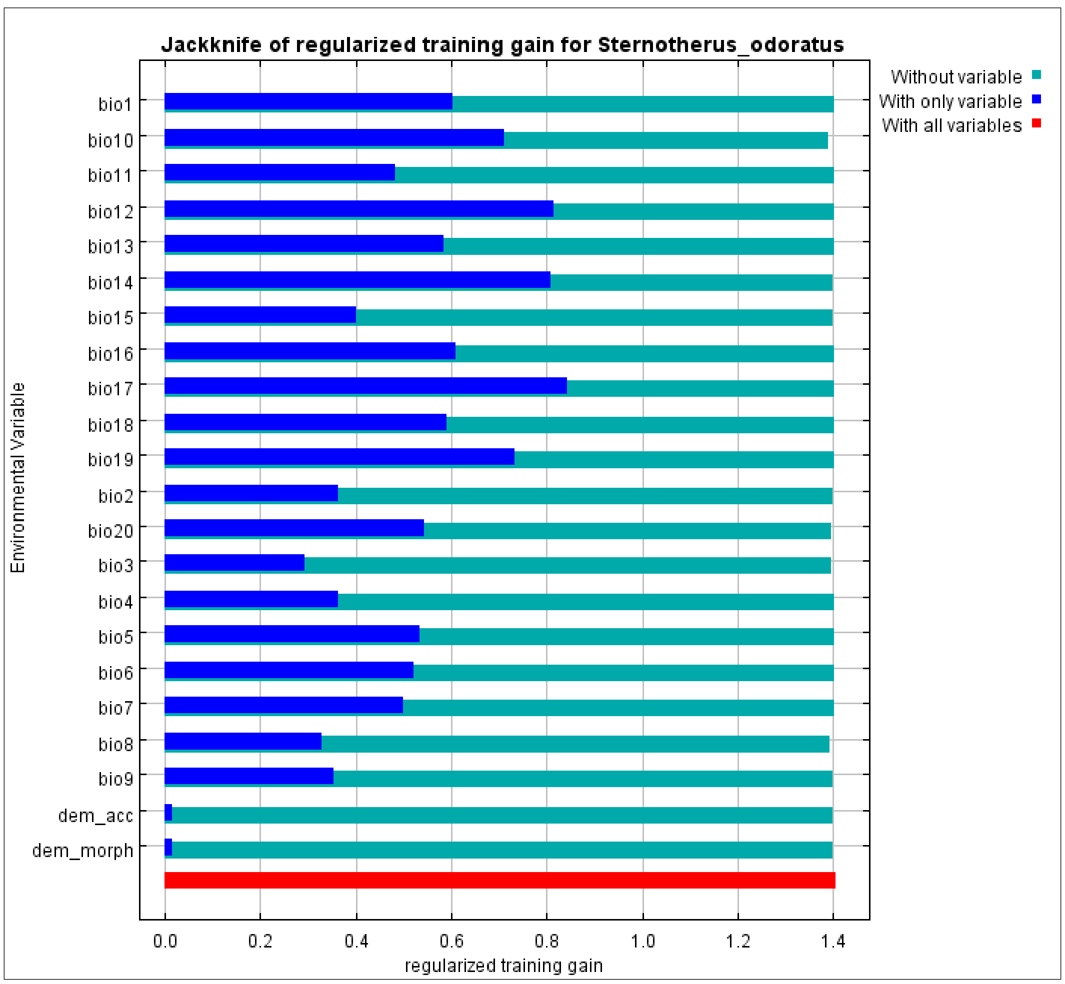


Together, the three charts in Figure 31 explain 87% of the musk turtle distribution. Note that the thresholds for the musk turtle are generally less severe than they were for the RCW and the ranges of between the thresh-

olds are broader. Perhaps the greater versatility suggested by those observations contributes to a better species survival possibility. These charts suggest that when it comes to climatic-change concerns, the turtle is more robust than the RCW. The results do not reflect weather events, particularly highly unusual weather occurrences. However, the data imply that when unusual weather events occur, the musk turtle is resilient to its most important climatic concerns. The musk turtles' ability to survive is most affected by extreme low precipitation and very high temperatures during the summer.

Once again, we can turn to an alternate estimate of which variables are most important in the model—the different "jackknife" analyses. Figure 32 shows the gains in viability based on the "training" locations. The red line at the bottom shows the complete musk turtle model with all variables for one submission.

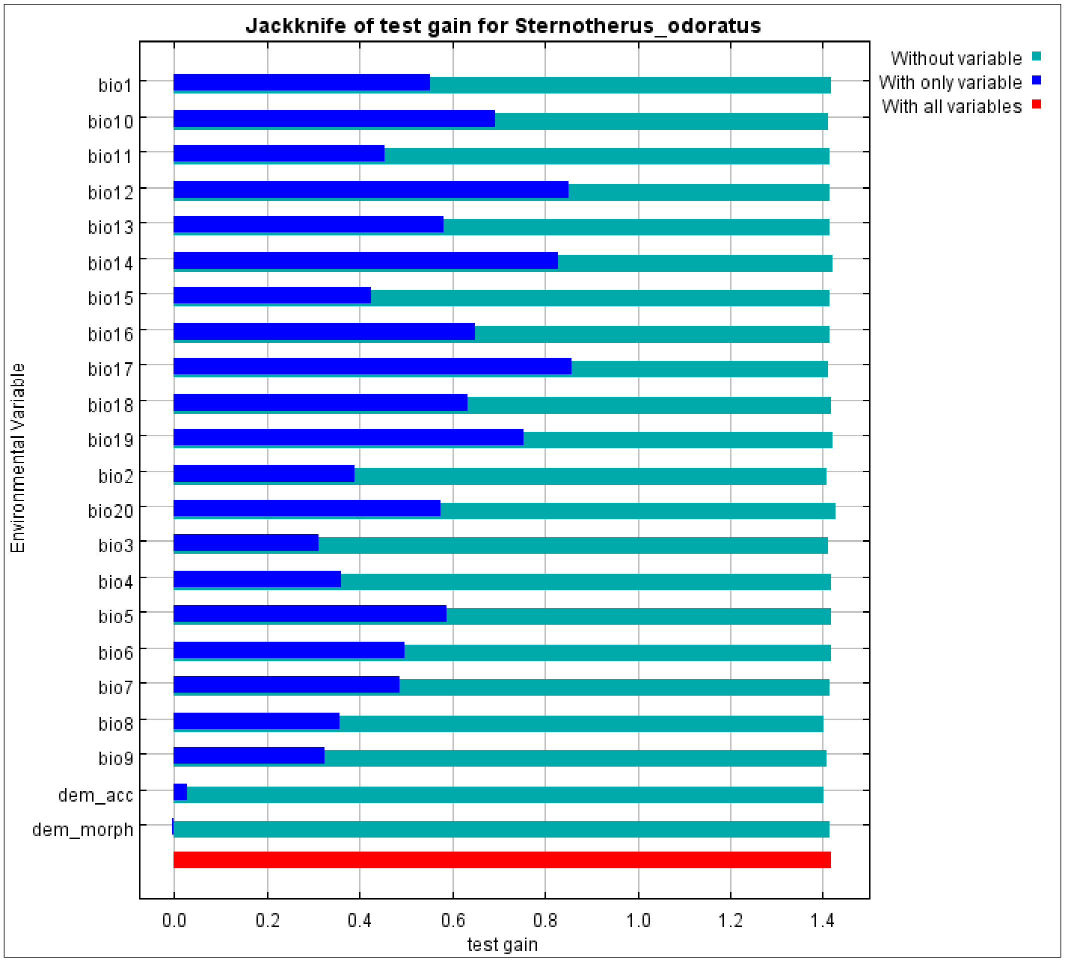
Figure 32. Jackknife analysis for the gains in viability based on the "training" locations.



The environmental variable with highest gain when used in isolation (the blue bar) is Bio17–Precipitation of Driest Quarter, which therefore appears to have the most useful information by itself. In this particular run, this is followed by Bio12–Annual Precipitation. Bio17 is in the top four in Table 17 above, but Bio12 shows up only in tenth place. On the other hand, Bio14–Precipitation of Driest Month, which is next in amount of contribution to the jackknife analysis, is second in importance in Table 17. The environmental variable that decreases the gain the most when it is omitted (the green bar) is Bio10–Mean Temperature of Warmest Quarter, which therefore appears to have the most information that is not present in the other variables. However, it appears that no variable contains a substantial amount of useful information that is not already contained in the other variables, because omitting each variable in turn did not decrease the training gain considerably. In general the "without variable" analysis stays about the same across the board, therefore eliminating one variable really is not important. In fact, for all three jackknife charts (Figure 32 – Figure 34), the "without variable" stays near the model maximum value (the red bar). This implies that dropping any one variable is not important; that the information lost from that variable is contained among the other variables.

Figure 33 shows the gains based on the "testing locations. Bio17 and Bio12 remain most important, and dem_morph the least important among the "with only" variables. Among the "without" variables there is little change in the bar lengths once again, so they have little effect.

Figure 33. Jackknife analysis for the gains in viability based on the "test" locations.

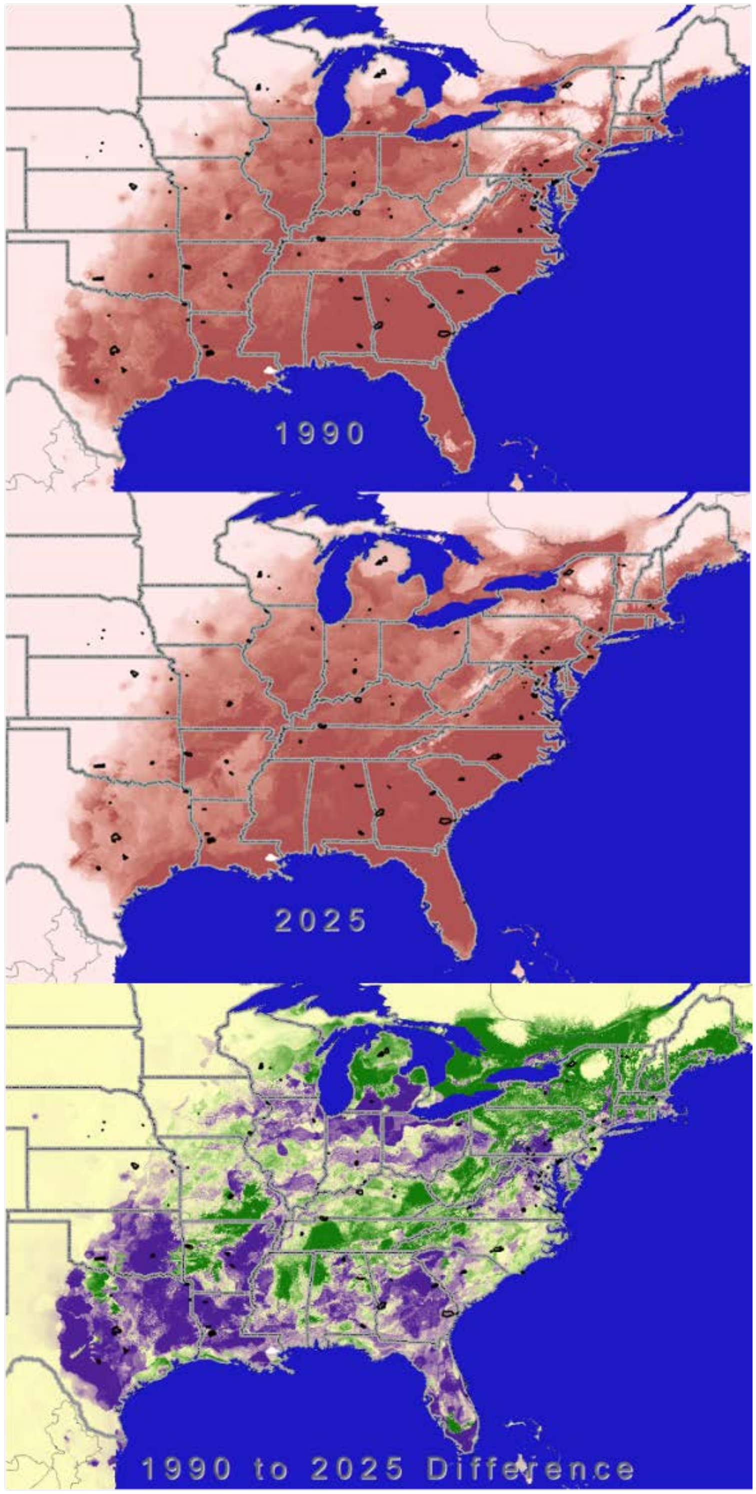


4.3 Musk turtle thresholds and climate change

4.3.1 Musk turtle distribution effects over entire range

The bioclimatic data for 2025 was submitted in order to see how different the potential distribution of musk turtle bioclimatic habitat would be by 2025. Figure 34 shows the initial 1990 distribution (top) the 2025 distribution (middle) and the difference between the two. Notice how definitively the south has lost its previously high-quality habitat areas (Fort Benning much more than Fort Stewart) while the middle portion of the eastern United States has improved, and Canada, Michigan, Pennsylvania, New York, and New England has greatly increased the distribution of quality musk turtle habitat.

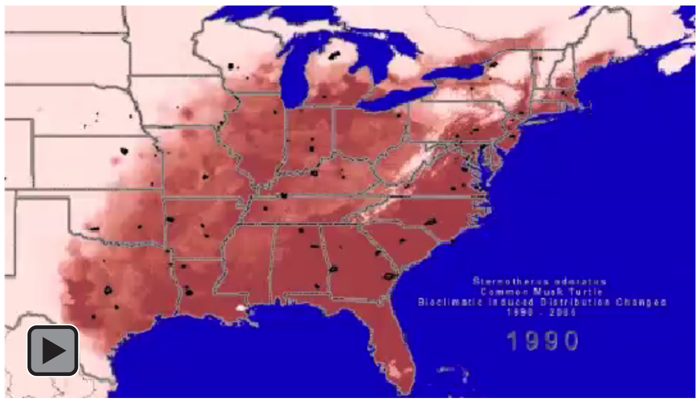
Figure 34. The initial 1990 musk turtle distribution (top), 2025 distribution (middle), and difference between the two (bottom); blues are decreases in desirable habitat distribution, greens are increases, and pale yellow represents no change).



In the longer time frame (Figure 35 animation) we can see that the musk turtle distribution tends to trend northeast and the best probability distri-

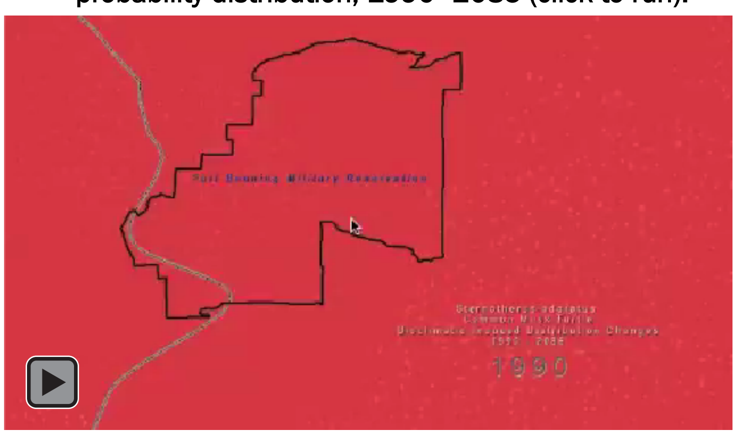
bution shrinks in the southeast and increases in the northeast by 2085. (Double click the file name and it will open the animation in internet explorer.) In fact southern Canada will have some of the best musk turtle habitat by 2085.

Figure 35. Animation of musk turtle probability distribution, 1990–2085 (click to run).



If this is the case, it is interesting to see what happens at the Army installations in detail. If we zoom in onto Fort Benning (Figure 36) and enhance the color table for that small region, a better idea of the problems the natural resources managers will be facing in a few decades can be seen.

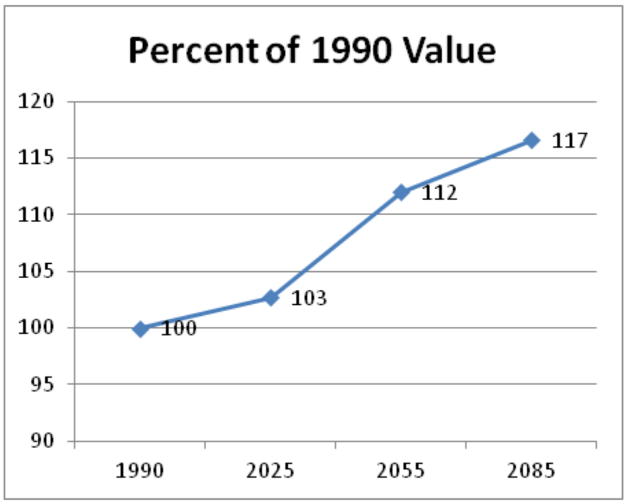
Figure 36. Animation of local area of musk turtle probability distribution, 1990–2085 (click to run).



The animations indicate that by 2085 the musk turtle distribution will shift from primarily the southeast to the middle of the eastern United states, and also to northeastern United States and southeastern Canada. To see how much the musk turtle distribution may change, and how, the probabilities at each time period were summed, and the chart in Figure 37 was generated showing a summary probability value for the turtle's entire range for each of the time slices available. Figure 37 shows that the habitat

of this resilient amphibian increases slightly in the near term (by 2025), by nearly 12% by 2055, and over 15% by 2085. Thus, the musk turtle potential existence will be enhanced by the predicted climate changes over its entire potential range. Whether the musk turtle will be able to take advantage of these changes by dispersal of its species across potential boundaries (lakes, roads, and cities) remains to be seen.

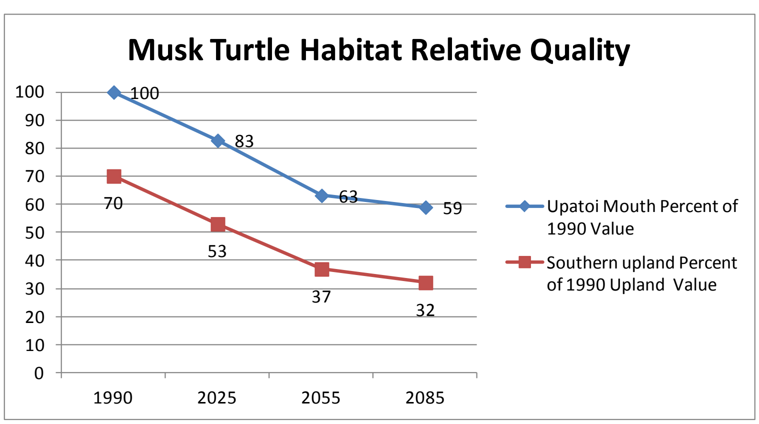
Figure 37. Summary probability value for the turtle's entire range for each of the time slices.



4.3.2 Fort Benning turtle habitat

Returning the focus to military installations, Fort Benning was considered prime musk turtle habitat in 1990. The value was 0.622 at a point near the mouth of Upatoi Creek, out of a possible 0.735 in its entire range. However, the quality of the range is projected to decrease by over 40% (down to 0.367) by 2085 (Figure 38).

Figure 38. Potential turtle habitat decrease at two Fort Benning locations.



What Figure 38 shows is that the musk turtle habitat decreases near the mouth of the Upatoi Creek much more dramatically by 2025 than was the case for the RCW in the same time period. Then the decrease continues but at a slower pace so that by 2085, 40% of the potential habitat at that location is lost. This means that if, in 1990, there was a musk turtle sighting once a week, in 2025 a musk turtle sighting at that same location may occur only once every 8.5 days, and by 2085 it may occur only about once every 12 days.

The analyses for the RCW and the musk turtle show that climate change will have both winners and losers in terms of species adaptation. For these two species, locally, Fort Benning will lose much of its habitat for these two species, whereas the musk turtle range will increase to the north.

4.3.3 Impacts on the habitat threshold ranges at other installations

After demonstrating how climate change will affect the range of the musk turtle, the next issues are to determine how bioclimatic changes affect the survivability of musk turtles at Army installations and whether climate change makes the job of preserving the musk turtle impossible for installation land managers. Using an approach similar to the one in Table 11, previously, an analysis of what will happen at all of the Army installations within the musk turtle range (plus a 100 mile buffer to be inclusive) was performed. Musk turtle range is defined as the Maxent probability level of 0.25 because this level most closely matches the "traditional" range as well as the default Maxent color table represented in Figure 24 (the first musk turtle range). Figure 39 below compares the original traditional range (black and yellow dotted line) with the Maxent-determined coverage (red area) at the 0.25 probability level.

Figure 39. The original traditional range (black and yellow dotted line) with the Maxent determined coverage (red area) at the 0.25 probability level.

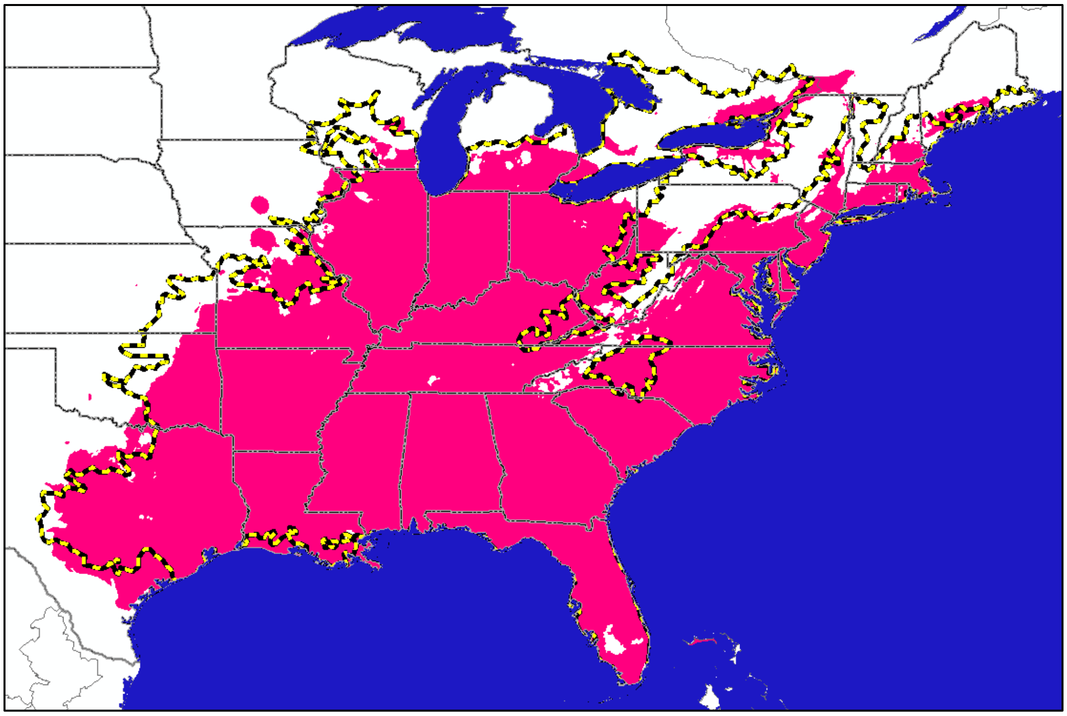


Table 18 presents the results for the two timeframes of 1990 and 2025. In the table, if a bioclimatic concern for that installation is below a threshold[13], it is color coded dark red; if it is above a threshold, it is color coded light red. The table shows those concerns that define 91.2% of the Maxent musk turtle model.

Table 18 Bioclimatic threshold modifications for the musk turtle

Bioclimatic Concern	Within Musk Turtle Range?	Mean Temperature of Warmest Quarter (10Xdeg C)		Precipitation of Driest Month (cm)		Precipitation of Driest Quarter (cm)		Isothermality (mean diurnal range/temperature annual range)		Precipitation of Coldest Quarter (cm)		Mean Temperature of Wettest Quarter (10Xdeg C)	
		Bio10		Bio14		Bio17		Bio3		Bio19		Bio8	
% Importance to Turtle Model		37.9		32.1		17.2		2.9		1.2		1.1	
Installation Name		1990	2025	1990	2025	1990	2025	1990	2025	1990	2025	1990	2025
Anniston Army Depot	Yes	253	268	75	72	265	271	40	39	388	393	78	106
Arlington National Cemetery	Yes	239	252	70	67	223	230	32	32	223	233	231	241

[13] Thresholds are from Table 17.

Bioclimatic Concern	Within Musk Turtle Range?	Mean Temperature of Warmest Quarter (10Xdeg C)		Precipitation of Driest Month (cm)		Precipitation of Driest Quarter (cm)		Isothermality (mean diurnal range/temperature annual range)		Precipitation of Coldest Quarter (cm)		Mean Temperature of Wettest Quarter (10Xdeg C)	
Army Chemical Center	Yes	233	246	74	73	248	255	32	32	251	261	212	223
Belle Mead General Depot	Yes	221	233	72	73	252	262	32	32	252	266	213	219
Camp Atterbury Millaty Reservation	Yes	229	244	65	55	227	210	31	32	227	234	209	182
Camp Bullis	Yes	275	290	44	35	147	138	40	39	147	149	232	237
Camp Joseph T. Robinson	Yes	265	283	79	70	258	245	35	35	295	298	163	173
Camp MacKall Military Reservation	Yes	253	265	74	73	243	254	39	39	281	291	253	262
Camp Swift N. G. Facility	Yes	279	294	46	36	174	161	39	37	178	181	234	238
Charles Melvin Price Support Center	Yes	250	267	49	50	177	186	30	30	177	186	229	196
Custer Reserve Forces Training Area	Yes	209	224	39	41	147	158	29	29	152	161	199	178
Fort A. P. Hill Military Reservation	Yes	237	249	76	73	242	248	35	34	242	253	237	240
Fort Belvoir Military Reservation	Yes	235	247	70	65	223	228	33	33	223	233	229	235
Fort Benjamin Harrison (Closed)	Yes	223	239	58	54	195	201	30	30	195	203	204	191
Fort Benning Military Reservation	Yes	264	278	53	54	209	222	42	41	342	345	104	182
Fort Bragg Military Reservation	Yes	251	263	70	72	233	245	38	38	272	281	251	262
Fort Campbell	Yes	248	264	74	64	248	240	35	35	338	342	141	129
Fort Chaffee (Closed)	Yes	262	281	45	44	172	174	37	37	172	177	241	219
Fort Devens (Closed)	Yes	200	213	87	78	268	260	31	31	282	295	40	24
Fort Dix Military Reservation	Yes	223	235	78	76	257	263	32	31	257	270	216	225
Fort George G. Meade	Yes	237	249	73	70	237	243	32	32	237	247	237	224
Fort Gillem Heliport	Yes	251	265	77	74	260	265	38	38	356	362	80	103
Fort Gordon	Yes	257	271	69	70	227	240	42	41	317	324	92	213
Fort Hood	Yes	282	298	40	32	142	134	36	36	148	153	230	239
Fort Indiantown Gap Military Res	Yes	214	227	69	67	224	232	31	31	224	234	193	203
Fort Jackson	Yes	258	271	70	71	228	243	39	39	284	294	258	270
Fort Knox	Yes	240	256	69	60	245	232	34	34	282	287	132	171
Fort Lee Military Reservation	Yes	244	256	80	75	248	256	36	36	256	269	237	247
Fort McClellan Military Reservation	Yes	249	264	77	73	269	276	40	40	393	398	75	103
Fort McPherson	Yes	251	265	77	74	263	267	38	37	357	363	78	103
Fort Monmouth Military Reservation	Yes	222	234	82	80	274	276	29	28	274	288	218	191
Fort Pickett Military Reservation	Yes	236	248	79	77	258	260	38	37	261	273	236	241
Fort Polk Military Reservation	Yes	269	284	102	84	318	284	40	40	422	405	111	105

Bioclimatic Concern	Within Musk Turtle Range?	Mean Temperature of Warmest Quarter (10Xdeg C)		Precipitation of Driest Month (cm)		Precipitation of Driest Quarter (cm)		Isothermality (mean diurnal range/temperature annual range)		Precipitation of Coldest Quarter (cm)		Mean Temperature of Wettest Quarter (10Xdeg C)	
Fort Ritchie Military Reservation	Yes	210	238	76	62	234	210	31	33	234	211	148	205
Fort Ritchie Raven Rock Site	Yes	210	222	77	73	238	245	31	31	238	247	147	175
Fort Rucker Military Reservation	Yes	263	277	73	72	260	272	42	40	385	387	111	186
Fort Sheridan	Yes	210	227	34	37	136	145	26	27	136	145	210	196
Fort Stewart	Yes	269	282	57	59	199	219	41	38	266	272	269	282
Fort Wolters	Yes	280	297	37	35	125	125	37	37	125	128	223	233
Globecom Radio Receiving Station	Yes	234	246	73	71	233	240	32	32	233	244	234	238
Greencastle Military Reservation	Yes	222	235	66	64	209	216	32	33	209	217	201	195
Hunter Army Airfield	Yes	268	281	48	53	188	206	38	35	240	246	264	277
Indiana Arsenal Army Ammo Plant	Yes	235	250	69	60	238	223	34	34	254	259	123	162
Joliet Army Ammunition Plant	Yes	220	236	36	37	137	146	28	29	137	146	199	186
LaPorte Outdoor Training Facility	Yes	216	232	48	51	174	183	28	29	174	184	216	186
Letterkenny Army Depot	Yes	219	232	68	64	213	219	32	32	213	221	198	185
Lexington-Blue Grass Army Depot	Yes	232	244	70	60	258	232	34	34	274	268	214	180
Longhorn Ordnance Army Ammo Plant	Yes	272	290	68	62	236	230	38	38	319	321	222	183
Louisiana Ordnance Plant	Yes	269	287	72	67	254	244	38	38	346	348	91	126
Malabar Transmitter Annex	Yes	271	281	42	41	171	161	46	42	171	161	271	274
Milan Arsenal / Wildlife Management	Yes	249	266	80	71	267	264	35	35	351	354	146	144
Military Ocean Terminal Sunny Point	Yes	257	268	73	76	263	277	40	39	301	308	253	264
Natick Laboratories Military Res	Yes	202	215	86	77	259	254	32	31	286	299	45	24
New Cumberland General Depot	Yes	227	240	70	65	220	226	30	31	220	229	205	192
Newport Army Ammunition Plant	Yes	228	244	55	54	193	200	31	31	193	202	209	206
Pine Bluff Arsenal	Yes	266	284	79	68	260	242	36	36	336	338	168	157
Radford Army Ammunition Plant	Yes	212	222	65	60	201	203	39	39	201	207	194	198
Ravenna Arsenal	Yes	204	218	55	56	192	198	31	33	192	198	184	192
Red River Army Depot	Yes	267	286	74	67	261	246	37	37	283	286	172	204
Redstone Arsenal	Yes	252	267	81	74	271	275	38	38	391	396	69	99
Rock Island Arsenal	Yes	229	245	29	32	111	119	26	27	111	119	229	219
U.S. Army Ammunition Depot	Yes	266	285	49	48	178	181	34	34	178	182	206	216
U.S. Army Reserve Center	Yes	207	219	82	79	260	259	29	28	321	335	12	35
U.S. Garrison, Fort Detrick	Yes	226	238	65	61	205	211	33	33	205	214	205	203

Bioclimatic Concern	Within Musk Turtle Range?	Mean Temperature of Warmest Quarter (10Xdeg C)		Precipitation of Driest Month (cm)		Precipitation of Driest Quarter (cm)		Isothermality (mean diurnal range/temperature annual range)		Precipitation of Coldest Quarter (cm)		Mean Temperature of Wettest Quarter (10Xdeg C)	
Vint Hill Farms Station Military Res	Yes	232	245	70	67	217	225	34	34	217	226	211	220
Warrenton Training Center	Yes	234	246	72	69	223	232	35	35	223	232	234	231
West Point U.S. Military Academy	Yes	202	215	83	84	271	283	29	29	271	286	135	149
Camden Test Annex	Barely	191	205	77	77	247	262	29	30	272	284	94	60
Fort Drum	Barely	187	201	61	61	204	218	28	29	226	239	86	88
Iowa Army Ammunition Plant	Barely	229	246	31	34	114	123	27	28	114	123	208	206
Kansas Army Ammunition Plant	Barely	254	273	35	34	121	123	31	31	121	123	190	204
Picatinny Arsenal	Barely	202	215	80	82	269	281	32	32	269	283	180	180
Savanna Army Depot	Barely	216	232	28	29	101	108	27	28	101	108	216	205
Seneca Army Depot	Barely	200	214	44	44	143	156	29	30	149	160	200	182
Aberdeen Proving Ground	No	239	249	73	71	246	251	32	31	247	258	239	227
Badger Army Ammunition Plant	No	205	221	25	25	87	92	27	28	87	92	192	210
Blossom Point Field Test Facility	No	240	252	71	68	231	234	33	32	231	242	240	241
Camp Dodge Military Reservation	No	224	242	21	22	75	80	27	28	75	80	204	209
Camp Grayling Military Reservation	No	181	194	30	32	116	121	29	31	116	122	170	179
Camp Johnson	No	196	210	44	46	148	164	27	28	153	168	196	205
Camp Williams	No	200	216	24	23	83	88	28	30	83	88	188	205
Edgewood Arsenal	No	238	251	73	71	245	250	32	32	247	257	238	229
Fort Ethan Allen Military Reservation	No	182	196	52	55	176	194	27	28	185	200	182	192
Fort Eustis Military Reservation	No	245	257	71	68	226	240	33	31	255	269	245	251
Fort Leavenworth Military Reservation	No	244	262	25	25	88	93	30	30	88	93	225	233
Fort Leonard Wood Military Res	No	236	254	50	50	188	194	35	35	188	194	177	176
Fort McCoy	No	199	215	23	22	80	85	28	29	80	85	187	205
Fort Monroe Military Reservation	No	250	262	73	72	234	248	30	29	260	274	245	257
Fort Riley Military Reservation	No	247	265	18	18	66	69	30	30	66	70	223	233
Fort Sill Military Reservation	No	271	288	27	24	95	93	35	34	95	94	208	224
Fort Story Military Reservation	No	247	259	73	73	238	249	31	29	262	275	243	256
Lake City Army Ammunition Plant	No	243	261	33	32	106	112	30	30	106	112	222	220
Sunflower Army Ammunition Plant	No	247	265	29	28	95	100	29	29	95	100	226	223

For Army installations that are within or on the edge of the 1990 musk turtle range, Table 18 shows that all will remain within the threshold limits for the turtle. Fort Polk is indicated to be above the Precipitation of the Driest Month threshold. But since the marginal response curve shows that the upper threshold really is not limiting, Fort Polk should have no problems in the 1990 to 2025 timeframe. Fort Stewart, Hunter Army Airfield, and Malabar Transmitter Annex will each have a problem by 2025 because they go over the Mean Temperature of Wettest Quarter threshold. Fortunately, this bioclimatic concern only contributes 1.1% to the model. Fort Riley is the only other location where problems appear in the Precipitation of Driest Month and Precipitation of Driest Quarter bioclimatic concerns. Since Fort Riley is not within the probability range of the musk turtle, this result is of no practical interest.

5 Summary and Recommendations

5.1 Conclusions

It was found that applying the Maxent procedure to the two species of Army interest resulted in objective, well justified definitions of the habitat extent and quality. Furthermore, the outputs supported answers to climate change questions that are useful for Army land managers.

The results of these analyses illustrate that there will be both "loser" and "winner" species in the face of climate change. The results indicate that RCW habitat will decrease by about 40% by 2085, but overall habitat for the musk turtle will increase by nearly 20%.

Below are specific conclusions addressing the applicability of the Maxent software package and the results of analyses of RCW and musk turtle populations up to about 70 years into the future.

5.1.1 Maxent performance

The traditional means of defining the distribution of a species has proved to provide contradictory, incomplete, and questionable results for analysis of species range change over time. For purposes of climate change studies and species management, an alternative to the traditional species range delineation was needed. The Maxent modeling program can define the ranges of species based on a multivariate statistical approach. The theoretical basis is derived from a first principle of physics—the Second Law of Thermodynamics. In this application, entropy is a measure of information content, so Maxent is designed to determine the maximum information content expressed by the data submitted to it. The software package was tested, and it was demonstrated that the outputs supported the research needs.

The analyses and tests presented show Maxent's effectiveness in delineating the probability distribution of species based on a series of inputs.

The statistical evaluations generated by the Maxent software of the viability of the models it outputs provide consistent, objective appraisals of the quality of the models generated.

Little variation was found between running the model many times or just once. The outputs were reasonably stable.

The marginal response curves provide thresholds for a species survival. Defining species thresholds objectively was a major investigative thrust of the overall research work package.

The thresholds in combination with the ranking of input-layer importance gives an individual the ability to objectively categorize which bioclimatic concerns will make the biggest difference for a species survival.

Surprisingly, the tests illustrated that some input layers that ranked in mid-importance had significant influences on the output probability distributions; they seem to be particularly significant on the local level.

Using Maxent to support climate change studies is very fruitful. By submitting to the model input data layers that reflect predicted changes, one can objectively follow the impacts of those changes on the distribution of a species.

5.1.2 RCW results

General

The model produced very similar results for the probability distribution among the 21 different runs submitted. The statistical evaluations of the models consistently showed a high level of likely confidence.

Maxent consistently indicated that the RCW northern limit was farther north than suggested by the GAP sample points submitted. If there is a more southern-northern limit to the RCW range, it is not due to any bioclimatic concerns.

The controlling bioclimatic factors are the precipitation of driest quarter (winter) and the annual precipitation. For the precipitation of driest quarter, the lower threshold is 18 cm of rain, but that is not a survival cutoff limit. The upper limit of 36 cm is a sharp limit, but above it the RCW will still survive. Annual precipitation is very important and severely limiting. For the mean annual precipitation, the lower threshold is 110 cm, a cutoff limit below which the RCW does not occur; the upper limit of 170 cm is also a sharp limit above which RCW will not survive. Annual precipitation,

therefore, is more important in limiting the RCW potential occurrence. The Mean Temperature of the Warmest Quarter is the next most important concern (14.5% contribution to the RCW model) followed by annual mean temperature (12.5% contribution). In combination, these four factors explain 86% of the RCW distribution shown by the model.

Restricting the input to the Maxent program to either the top four most-important inputs or the bottom four least-important inputs still provides a similar probability distribution. It can be said that the more inputs used, the more restricted (better) is the definition of the species-distribution results.

Adding additional inputs (e.g., land cover) as layers to the Maxent analysis will further restrict and better define the probability distribution. Most experts limit RCW habitat to outside of the Mississippi valley area. The Maxent probability includes this area within the RCW distribution, but at a less-intense level. The addition of other concerns (i.e., land cover, physiography) further decreases the RCW presence in the Mississippi valley, but does not limit it entirely. Therefore, if the RCW does not occur in the Mississippi valley, some other factor than those considered in this research is causing the restriction.

Climate change will result in a 9% decrease in the RCW habitat by 2025 and a 40% decrease by 2085.

Use of the bioclimatic inputs from each of six Global Climatic Model (GCM)/scenario combinations instead of the “average scientific consensus” value did not alter the results significantly. A few more potential problems surfaced that the averaging had suppressed, but the general trend of the modeled climatic effects are evident in the consensus analyses.

Army impact

Of those Army installations that already host RCW populations, the top 15 are and will remain within the threshold limits for the RCW

At Fort Eustis, the annual precipitation is currently too low for RCW, but by 2025 it will increase so the RCW will be more at home there.

Seven Army installations (Fort Polk, Fort Stewart, Hunter Army Airfield, Longhorn Ordnance Plant, Louisiana Ordnance Plant, Pine Bluff Arsenal,

and Red River Army Depot) that are currently within all of the thresholds will move above the threshold for the important concern of Mean Temperature of Warmest Quarter. This represents a bioclimatic threat to the continued existence of the RCW at these locations. The threshold cut is considered "extreme," so passing the threshold is highly significant. Longhorn will be more than 1 °C above the threshold. Land managers will have a difficult time persevering RCW at these installations, even applying an intensive level of effort.

5.1.3 Musk turtle results

General

The range of the musk turtle is extensive, covering most of the eastern United States.

The Maxent outputs suggest that the musk turtle is a hardier species than the RCW. Unlike the RCW, near-term climate change will increase its range by about 3% and encourage it to move toward the north. As the range trends northward, traditional habitat areas in the southern United States will decrease in quality.

Warmth and dryness matter most to the musk turtle:

- Bio10–Mean Temperature of Warmest Quarter provides a 35.8% contribution to the Maxent model
- Bio14–Precipitation of Driest Month provides a 32.7% contribution to the Maxent model
- Bio17–Precipitation of Driest Quarter provides a 17.2% contribution to the Maxent model

The input layers that best enhanced the musk turtle model were the hydrologic accumulation layer and landform morphology derived from the topographic data. These two contributed to the local variations more than modifying the extent of the entire range.

Army impacts

All Army installations will remain within the threshold limits for the turtle through 2025.

Fort Stewart, Hunter Army Airfield, and Malabar Transmitter Annex will each have a problem by 2025 because those locations will exceed the Mean Temperature of Wettest Quarter threshold. Fortunately, this bioclimatic concern only contributes 1.1% to the model. Therefore, it is not anticipated that the Army will need to fund a musk turtle habitat maintenance program related to climate change by 2025.

It is noted that even for the musk turtle, there will be localized losers in the overall population. At Fort Benning, habitat will decrease by about 40% for the musk turtle near the mouth of the Upatoi Creek by 2025.

5.2 Recommendations

The application of Maxent software to the question of climate change impacts on species of interest to the Army provided objective and supportable results using a cost-effective methodology. Therefore, it is recommended that:

- the demonstrated Maxent analysis methodology be applied to additional species of Army interest to identify habitat changes
- researchers check Maxent distribution patterns against ground-truth surveys to validate the probabilities

At Fort Polk, Fort Stewart, Hunter Army Airfield, Longhorn Ordnance Plant, Louisiana Ordnance Plant, Pine Bluff Arsenal, and Red River Army Depot, which currently fall within all of the RCW thresholds, climate change will move Mean Temperature of Warmest Quarter above the RCW threshold. At those locations, there will be no feasible way for Army land managers to mitigate the negative impacts of climate change. Therefore, it is recommended that the Army consider requesting that the U.S. Fish and Wildlife Service reduce the Army's obligation to carry out RCW recovery programs at those installations.

Because all Army installations will remain within the threshold limits for the common musk turtle through 2025, there will be no need to expend funds to promote musk turtle habitat maintenance to mitigate climate change impacts.

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14. ABSTRACT

Army installation managers and planners have limited sources of scientifically reliable information that can be used to examine potential climate impacts on local flora and fauna. The present work evaluated the viability and versatility of applying statistical multivariate analysis to define the current and projected future range probability for species of interest to Army land managers. A software program called Maxent was used to perform range-extent analyses for two animal species of interest to Army land managers: the Red-Cockaded Woodpecker (RCW) and the common musk turtle. The technology was used to determine how climate change might affect species thresholds of survival at Army installations. The software data input requirements and output capabilities are described. The analytical methodology applied to the study of both species is discussed in detail, and validation of results is addressed.

The authors conclude that Maxent analyses can provide impartial, data-based results that reflect scientific consensus on related climate-change issues while avoiding emphasis on the extremes of scientifically collected data. Analysis results indicate that climate change will alter RCW habitat threshold values on some installations beyond the point where Army-managed mitigation is possible. In contrast, musk turtle habitat will increase at least until 2025.

15. SUBJECT TERMS
climate change impacts, evaluation, land management, habitat, Red-Cockaded Woodpecker, common musk turtle, Maxent software

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